UNIVERSITY OF LJUBLJANA
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MASTER'S THESIS

JET FUEL PRICE RISK HEDGING STRATEGIES: THE CASE OF US AND EUROPEAN FUTURES MARKETS

Ljubljana, March 2021 ALEKSANDAR DMITRIĆ

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LIST OF ABBREVIATIONS

sl. – Slovene

ADF – (sl. razširjeni Dickey-Fuller); Augmented Dickey - Fuller

AIC – (sl. Akaikeov informacijski kriterij); Akaike Information Criterion

BIC – (sl. Bayesijski informacijski kriterij); Bayesian Information Criteria

DF – (sl. Dickey-Fuller); Dickey - Fuller

ECM – (sl. Model korekcije napak); Error Correction Model

EFPT – (sl. Borza za trgovanje s sorodnimi pozicijami); Exchange for Related Position Transactions

GARCH – (sl. Splošni model avtoregresivne pogojne heteroskedastičnosti); Generalized Autoregressive Conditional Heteroscedasticity

ICE – (sl. Medcelinska borza); Intercontinental Exchange

KPSS – (sl. Kwiatkowski-Phillips-Schmidt-Shin); Kwiatkowski-Phillips-Schmidt-Shin

NYMEX – (sl. Newyorška merkantilna borza); New York Mercantile Exchange

OLS – (sl. metod navadnih najmanjših kvadratov); Ordinary Least Squares

VECM – (sl. Vektorski model korekcije napak) Vector Error Correction Model

WTI – (sl. teksaška lahka nafta); West Texas Intermediate

WHO – (sl. Svetovna zdravstvena organizacija); World Health Organization

USD – (sl. ameriški dolar); United States Dollar

INTRODUCTION

Jet fuel is a major component in total operational costs for any airline company. The exact share is difficult to determine precisely but various research suggests, that anywhere from 15 – 40 % of the total operational costs in a typical airline company can be attributed to jet fuel (Swidan & Merkert, 2019). To make things worse, it is quite difficult to predict the amount of the total fuel costs, even though the companies are able to determine total quantities of fuel they would need in any given year. This is because jet fuel price levels are highly volatile, as the price is influenced by various factors. These include, but are not limited to crude oil price movements, jet fuel's accessibility, as well as present and anticipated global jet fuel demand. One way any given airline company can protect itself against unpredicted spikes in cash outflows is to try and flatten the patterns of its major expenditure categories. Hedging is used to lock in the costs of future fuel purchases, which protects against sudden cost increases from rising jet fuel prices. Risk Management Departments employ various hedging strategies according to firms' risk preferences (Smith & Stulz, 1985).

Typical ways of managing jet fuel price exposure among some major airlines have been by using financial derivatives. One problem that occurs, however, is that markets with derivatives on jet fuel are not nearly as liquid as those on other oil distillates, which reduces the pool of possibilities when it comes to constructing a good hedge programme. Although it is possible to avoid this issue by entering into one or multiple *Over The Counter* (OTC) contracts, associated illiquidity premium could be quite substantial. Instead, airlines and investors alike, employ the practice of cross hedging, where they use financial instruments such as futures on alternative oil products as the underlying asset (Morrell & Swan, 2006). For the cross hedge on jet fuel to be successful, the price of the underlying asset in the chosen instrument needs to be highly correlated with that of the jet fuel (Saunders & Millon, 2008). Moreover, the hedge ratio needs to be calculated to determine the exact number of the futures contracts to be bought. The optimal hedge ratio is the one that minimises the variance of the hedged portfolio (Juhl, Kawaller, & Koch, 2012). Although numerous researchers have proposed techniques to be used in the estimation of the optimal hedge ratio, the airlines still approach hedging rather cautiously and only some of them decide to hedge most of their fuel expenses consistently. Reasons for this are numerous, and they range from companies' respective business models, high costs associated with maintaining a successful hedge or institutional prohibitions.

There is no doubt that a sound and effective plan for jet fuel cost control is in the focus of every airline's upper management. Financial hedging is just one of the approaches that can be chosen and pursued, and even there, there are myriad ways how it can be constructed. The issue is that neither the business community nor the literature identify one single, optimal approach to it. Although the effect of financial hedging can be traced through publicly available financial reports, the exact structure of a successful hedge programme is always treated as a business secret. That is probably the reason why there are practically no recent studies that investigate the structure of portfolios actually used by the most successful hedgers among the airline companies. Instead, researchers try to investigate and present the most effective ways of how specific types of financial derivatives can be used for the purpose of jet fuel hedging.

One such article inspired me to research this topic myself. Turner and Lim (2015) investigated the North American Commodity Futures Market for the purpose of jet fuel hedging using various modelling techniques and very long data series. However, given the substantial changes that reshaped the supply side of the oil market throughout the last decade, in this thesis, I decided to use a relatively shorter, recent series of data, as these give more useful information necessary for establishing an effective hedging programme. Finally, it appears that most of the existing literature on the subject emphasise its theoretical dimension without giving some useful guidelines to the potential practitioners. This thesis is, therefore, purposefully written to contribute to the existing literature on the subject, but, at the same time, aid potential practitioners to develop their own hedging programmes. It covers both the theoretical and practical sides of the matter by explaining what econometric models should be used, and by giving phased guidelines on how this is done with the real data.

Research questions elaborated in this thesis address fundamental issues, with regards to organising a cross hedge using futures contracts in the European and the US markets:

1. What are the optimal maturities for contracts used in jet fuel hedging on the US and European markets?
2. Are there substantial differences in the choice of the underlying commodities used in futures for jet fuel hedging between the American and the European markets?
3. Does the Error Correction Model (ECM) give superior estimates of optimal hedging ratios compared to the Ordinary Least Square (OLS) method?

The year of 2020 was in all senses atypical for the global aviation industry. The ongoing corona virus pandemic caused a significant decrease in international travel from the moment national governments first decided to impose strict travel restrictions. Although full-service network carriers are expected to experience somewhat more of the damage compared to the low-cost carriers given the traditionally international character of their operation, both groups of operators were bound to sustain significant losses from their jet fuel hedge programmes, had they not managed to close their open positions on time. The losses can be attributed to over hedging and subsequent payment for the unused jet fuel, and to the periods of significant and unanticipated jet fuel price decrease. According to a study on the effect the ongoing corona virus pandemic is expected to have on the global aviation industry, readiness of an airline to stimulate demand pricewise aggressively is recognised to be a particularly important lever to be used once the travel bans are lifted (Sanchez, Dorta, & Escofet, 2020). This thesis can help mitigate the risks of this happening. Hedging jet fuel with futures contracts can be particularly advantageous, because such an arrangement does not require prepayments and purchase guarantees and all the open positions can be closed in an instant if needed.

Data that were used in this thesis consists of the closing values of futures contracts on referent types of the crude oil and oil derivatives with various maturities, linked together in series that span the period from 2015 – 2019. Series of referent jet fuel daily quotes were retrieved as well. No data from 2020 were used, as this would misrepresent the usual data dynamics and serial interdependencies severely. All the data were retrieved from the Bloomberg terminal. The series were then prepared for further analysis, and the vital parameters were estimated using Ordinary Least Squares (OLS) and Error Correction Model (ECM). Data transformation and estimations were performed using the Python Programming Language and Jupyter Notebook environment, and all the used functions can be found in the Appendix 3 of this thesis.

The thesis is organised in the following way: The first section provides a short overview of the literature covering the topic of jet fuel hedging, while the second section presents various financial derivatives that can be used in jet fuel hedging. The third part is dedicated to presenting the data and methodology used in this research, and the fourth section presents the obtained results. The fifth section draws attention to some of the changes that the currently ongoing pandemic of the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is bringing to the aviation industry, while the conclusion is presented in the final section.

1 LITERATURE OVERVIEW

There is a significant amount of literature that explores mathematical theory and the logic of hedging in both financial and nonfinancial firms, developed in the second half of the twentieth century (Johnson, 1960; Ederington, 1979; Rao, 1999). Early works on this subject consider financial and non-financial companies in general, suggesting avoidance of high direct costs of financial distress and reduction of financial distress' probability as the main reasons why firms hedge their costs (Smith & Stulz, 1985). Contributions to the idea of hedging in the airline industry in particular are also numerous. The idea that was particularly elaborated is the market premium that the hedged airlines were most commonly associated with. This premium comes as the signal of acknowledgement from investors, who value corporate decisions intended to make cash flows more stable and predictable. (Carter, Rogers, & Simkins, 2006). By means of hedging, the company predicts its future earnings more accurately, and is, therefore, better prepared to make potential investments even in the high stages of the fuel price cycles (Cobbs & Wolf, 2004). Morell and Swan introduced a more elusive reason for the premium. They claimed that a well-organised hedging activity is an inexpensive signal to both present and future investors that the management is technically competent and alert (Morrell & Swan, 2006). This connection between hedging behaviour and gains in corporate value of the major US carriers was investigated further in a more recent study by Treanor et al. They find that airlines tend to hedge more when fuel prices are high and rising, and that investors, in fact, value subsequent increases in the volume of hedged fuel more than the particular hedging practice itself (Treanor, Rogers, Carter, & Simkins, 2014). Reduction of operating costs might be one of the most apparent reasons for jet fuel hedging, but studies seldom find strong, supporting evidence for this claim (Lim & Hong, 2014). In fact, one study has shown that operational hedging should be deployed in conjunction with financial hedging for effective reduction of the operational costs (Swidan & Merkert, 2019).

The financial crisis of 2008 and subsequent wild swings of jet fuel prices made the practical aspects of a successful jet fuel hedge of particular interest. Researchers have become more motivated to study fine tuning of effective models, ones that will incorporate as many of the important data patterns as possible. In a study that focuses on cross-hedging with OTC instruments, such as forward contracts, Adams and Garner investigated the benefits of using more sophisticated models compared to the classical Ordinary Least Squares (Adams & Gerner, 2012). Namely, they wanted to see whether accounting for heteroscedasticity in error terms from a regression and long-run relationship in price movements between the jet fuel and the hedging instrument gave better estimates of the optimal hedge ratios, compared to the simpler OLS model. Their analysis shows that both Generalized Autoregressive Conditionally Heteroscedastic model (GARCH) and Error Correction model (ECM) give superior optimal hedging ratios compared to those obtained from OLS. Their findings are particularly interesting, as they showed empirically that crude oil is an inferior commodity for cross-hedging of jet fuel compared to the middle distillates. They also showed that middle distillates' effectiveness decreases as maturity of the used contracts increase, making other considerations such as liquidity of an instrument become more relevant. Another article revisits this idea of model suitability concerning minimum variance hedge ratios and jet fuel cross hedging and reports different results (Turner & Lim, 2015). The authors have, namely, applied hedging efficiency tests to the optimal hedge ratios calculated using OLS, ECM, GARCH and GARCH with an error correction model and artificial series of data made by Monte Carlo simulation from real data on the futures contracts. They found no significant differences in hedge effectiveness provided by the hedging ratios estimated by OLS or any of the more sophisticated models. In fact, they found no model that generates superior hedging ratios consistently compared to the others.

2 FINANCIAL DERIVATIVES USED IN JET FUEL HEDGING

2.1 On the purpose of jet fuel hedging

Fuel hedging is one of the methods the airlines can use in an attempt to level their variable costs in a predictable way. It is very similar to when other companies monitor and control their interest rate exposure, foreign exchange risk, or credit exposure. Fuel hedging allows airlines to set level prices and create foundations to long term planning. It is important to understand that the goal of fuel hedging is not to speculate in oil prices and/or make money on the trade (Morrell & Swan, 2006). The objective is rather to set the level price point for their fuel expenses, so that companies can make long term strategies. One of the downsides of fuel hedging is that it can be quite expensive to organise and manage successfully. In this chapter, I shall present swaps, options, forwards and futures contracts, which are the derivatives most commonly used in Risk Management (Eydeland & Wolyniec, 2007). Each one of them has its pros and cons, and it is up to the Risk Management Department of the company to make the perfect blend of instruments that corresponds to the firm's risk profile optimally.

2.2 Swap Contracts used for the purpose of jet fuel purchases

A Swap Contract is an agreement where two parties agree to exchange two future streams of cashflows, one of which is based on a fixed (predetermined) price, and the other on a floating (variable) price (Kaminsky, 2012). The fact that the parties arranging a swap are free to negotiate all of the terms of the Contract according to their particular needs, and that the validity of the deal does not necessitate an exchange to supervise the process[1], makes swaps purely OTC instruments where the parties involved must account for the counter party risk[2]. The involved parties, usually create the entire agreement in accordance with the

[1] In practise, Swap Contracts are usually arranged through a swap dealer who acts as a link between the parties.
[2] After the enactment of the Dodd-Frank Wall Street Reform and Consumer Protection Act in July of 2010, major swap participants are now being overseen by the Commodity Futures Trading Commission which

International Swaps and Derivatives Association's Master Agreement[3] which, among other details, specifies the collateral requirements for each participating party in the Contract. Although collateral requirement helps in credit risk mitigation, it is optional in a standard Swap Contract. Swap Agreements must specify precisely when the cash flows are to be paid and the way in which they are to be calculated (Hull, 2015). Swap Contracts can be financial, which are settled in cash, or physical, which require actual delivery of the commodity (Kaminsky, 2012). Since the exact features of every contract are completely customisable, a complete and precise classification of the types of Swap Contracts does not exist.

In the aviation industry, airlines can arrange Swap Contracts directly with jet fuel suppliers (physical swap), or they can arrange pure financial Swap Contracts with any interested party. In the following text I shall specify the mechanics of the former.

Both cargo and passenger airliners must fuel their airplanes before almost every flight. Since the biggest fuel suppliers, such as World Fuel Services Corporation or Air BP, are present worldwide, an airliner might be interested in arranging a physical Swap Contract for a certain period of time, to cover all fuelling carried out wherever the supplier offers its services. Having predictability in the operative costs is an important lever for any management. It makes setting goals and preparing pricing strategies more tangible and accurate. A Swap Contract on jet fuel would achieve exactly that. On the other hand, fuel suppliers can have a strong incentive for participating in a Swap Agreement, as it would assure exclusivity in supply with the client for a certain time period, which, consequently, assures positive cash flows and revenues.

To set up a basic commodity Swap Contract, the following Contract items should be specified by the participating parties (Kaminsky, 2012):

1. The underlying commodity;
2. The notional quantity (volume);
3. The fixed price;
4. The published price benchmark for floating price;
5. The settlement date(s);
6. The cashflow dates.

Let us assume that a private air operator decides to enter into a Swap Contract with a major jet fuel supplier that offers its services on all of its locations of operation. Two companies agree that the operator can uplift up to 200,000 gallons of jet fuel within the following two months and pay for it a fixed price of $2.90 per gallon of fuel, no matter what the actual market price is at the moment of fuelling. The benchmark price for this arrangement is

requires swap dealers to demand appropriate collaterals from their clients and to conduct daily marking-to-market on their accounts (Miller & Ruane, 2012)

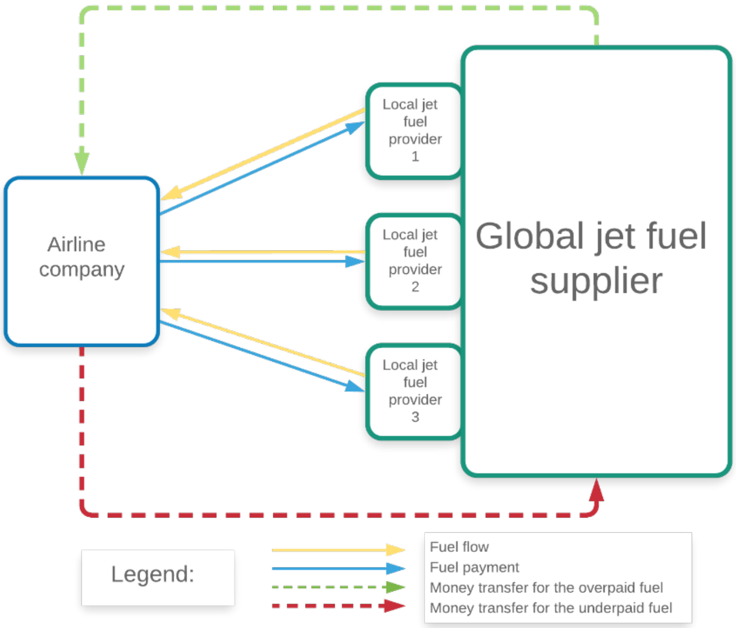
[3] Details can be found on the following link: https://www.isda.org/protocols/

decided to be the internationally recognised Standard, Platts Global Jet Fuel Index[4]. The airline would fuel its aircraft as needed and pay the spot market price for this service to the local fuel provider, who the fuel supplier from the Swap Contract already has an arrangement with. At the end of each of the week in the contracted period, the parties would transfer payments to each other, according to the following formula (Eydeland & Wolyniec, 2007):

$$Payment = Volume * (AverageWeeklyPrice - SwapPrice) \qquad (1)$$

Where *Volume* represents the amount of fuel uplifted during the week in gallons, and *SwapPrice* is the fixed, contracted price of \$2.90. Finally, *AverageWeeklyPrice* is the average of that week's floating, benchmark price. In case the operator paid higher than the average price, i.e. *(AverageWeeklyPrice – SwapPrice) > 0*, the supplier would have to reimburse the operator for the entire exceeding amount. On the other hand, if the operator paid lower than the average price for the fuel it uplifted, the reimbursement would go in the opposite direction.

Figure 1: Swap Contract diagram: Links between an airliner and a jet fuel supplier



Source: Own work.

The airliner could make a swap with the same purpose even without the fuel supplier on the other side. The Contract would be a purely financial arrangement, where the participating parties basically bet on the future fuel costs and then transferred the underpaid / overpaid

[4]https://www.spglobal.com/platts/plattscontent/_assets/_files/en/our-methodology/methodology-specifications/world_jet_indexes.pdf

amounts accordingly. It is the industry's practise to refer to the fixed price payer, the one who would benefit from the price increase, as the buyer of the Swap. This party is said to be assuming the long position in the Contract, while the floating price payer is consequently short selling the Swap.

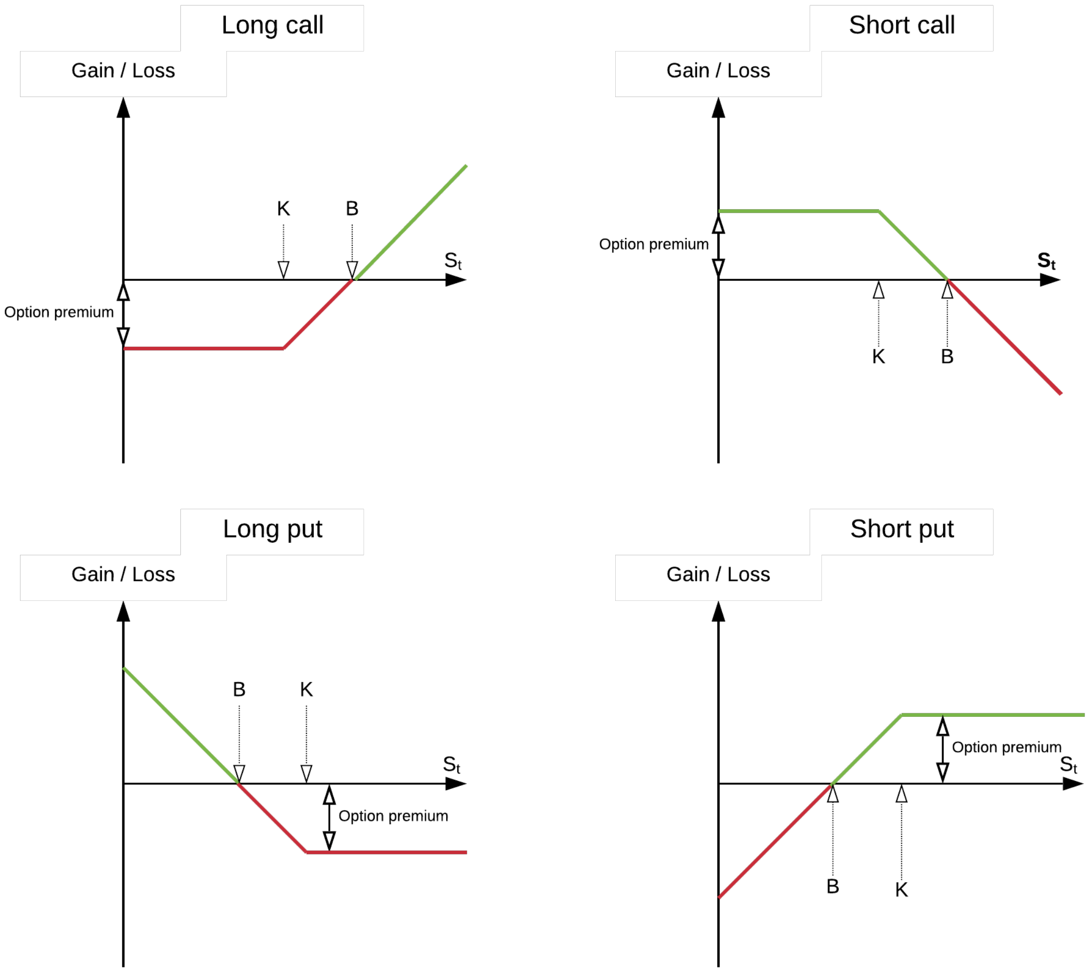
The example presented before is a typical *plain* or *vanilla Swap*. If the airliner's management team does not take into account that the fuel might actually get cheaper within the contracted period, the same Swamp Contract can turn out to be a perfect trap, and potentially a very expensive lesson. Namely, whenever the average weekly reference price is below the fixed swap price, it will be the airliner who has to top up the supplier's account. In other words, the Swap buyer will never be in position to enjoy the underlying commodity's lower market price. *Participation Swaps* may be a solution for adverse price movements. With Participation Swaps, the party that buys at the fixed price is still fully protected when the prices of the underlying commodity rise over the agreed swap price. However, if the price goes under the agreed fixed swap price, the party only participates in the transfer by an agreed amount. Consequently, the airliner which enters into such a contract will probably find the fixed price quoted for this Participation Swap Contract to be somewhat higher than in a plain vanilla swap (James, 2008).

2.3 Hedging jet fuel expenses with options

Options are a slightly more complex group of financial instruments available to be used in energy markets for hedging jet fuel costs. An option is a Contract Agreement that gives its holder the right, but not the obligation, to buy (a call option) or sell (a put option) another financial instrument, goods or commodity – all of which is referred to as the underlying, at an agreed price by or on a certain date (Kaminsky, 2012). This agreed price at which the option can be activated is known as a strike or exercise price. The date an option is to be exercised by is referred to as the maturity or expiration date. The party that issues and sells options is called an option writer, while the buyer of an option is referred to as an option holder. The price that a buyer pays to the option writer is called an option premium.

There are many ways how options can be classified, and it all depends on the criteria that we are interested in. *American style options* are those that can be exercised at any moment from the time of the purchase up until the expiry of the Contract. *European style options,* on the other hand, can only be exercised at maturity. Because of this flexibility that American options give to their holders the premia paid for their purchase are usually higher (James, 2008). Options can be acquired both on an exchange and OTC. To be able to use the benefits of options traded on an exchange market, participants must maintain a margin on their accounts up to a certain percent of their contractual exposure. This is why trading specially tailored options over the counter is much more convenient for the airlines that hedge and other non-financial entities, as it eliminates the necessity for potentially substantial amounts of liquid funds to be allocated daily to accounts at a clearing house. However, parties that trade options OTC take all the counterparty risk. As with the other OTC instruments, these options are often highly customised to fit the specific needs of the parties involved. To make it easier to explain the two very specific types of options suitable for jet fuel hedging, we should first analyse the payoff profile of the basic call and put options at their expiration / or at their exercise moments.

Figure 2: Call and put option payoff diagram



Source: Own work.

Both option types require two willing parties to lock the Contract. An investor can either take a long position (which is to buy an option), or he can take a short position (i.e. sell / write an option). Once the option is purchased, the writer receives an option premium and becomes liable under the terms of the Contract to sell or buy the underlying asset at the strike price in the moment of the exercising. The above illustrations on the Figure 2, show payoff profiles for both long and short positions in a European style Option Contract at its maturity, or, in the American style Option Contract, at the moment of the exercise. Let K be the agreed strike price and S_t be the actual price of the underlying asset at any moment up until the option's expiry / exercising. The option holder's total payoff starts with the cost in the amount of the premium paid, which, by the same token, is the initial gain of the option's writer. Subsequently, the expected payoff[5] from a long position in a European call option is: Max (S_t – K, 0), whereas the payoff of the writer is just the opposite: - max (S_t – K, 0) = min (K – S_t, 0). This reflects the fact that the option holder will only exercise his option in the event when $S_t > K$, which is referred to as the option being *in the money* (Hull, 2015, p. 220). Similarly, the holder of a European put option will only exercise his option when it is in the money, that is if at the maturity $K > S_t$. His payoff will be max (K - S_t, 0) while, at the same time, the writer's payoff will be: – max (K – S_t, 0) = min (S_t – K, 0). A call option is referred to as being *at the money* when $S_t = K$ and out of the money when $S_t < K$, while the put option is at the money when $S_t = K$, and out of the money when $S_t > K$. Finally, as it is apparent from the illustration, in order for an option holder to realise a gain from the Contract, no matter if the option's type is a call or a put, the respective option has to be in the money at the moment of the exercise by a sufficient price difference, as this way, the holder will also cover the initial costs of the option purchase. This break-even point in the gain / loss function is marked by the letter B on Figure 2.

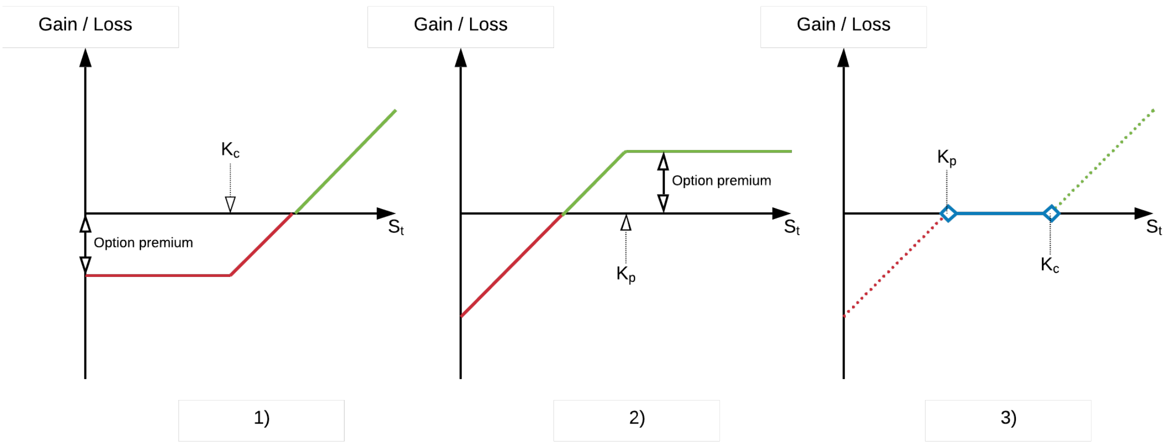
One of the option types with a more complex payoff profile is the Asian option, characterised by a time window during which an average price for the underlying asset is calculated. This averaging window is specified precisely in every Contract, so the payoff profile from a long Asian call option is max (average (S_t) – K, 0) and max (K – average (S_t), 0) from the Asian put (Kaminsky, 2012). Finally, jet fuel hedgers can use spread options, which are options on the price difference between two commodities. For hedging of jet fuel, a good choice would be the so-called crack spreads, where one of the two commodities is crude oil and the other is one of its distillates, such as gasoline, heating oil or jet fuel itself. The payoff profile from a long position in a call on spread is max (($S_t^1 - S_t^2$) – K, 0) and from a long in put on spread it would be max (K – ($S_t^1 - S_t^2$), 0), where S_t^1 and S_t^2 are two forward prices on expiration for two commodities, expressed in the same units (Geman, 2013).

Finally, one of the most important features of any Contract on the energy market has to do with the amount of the underlying commodity that is covered in the Contract. To account for that, the industry has developed a special class of options that, although characteristic for natural gas markets, can be found in other markets as well, mostly in the form of provisions embedded in the long-term contracts and asset-related transactions (Kaminsky, 2012, p. 151). They are typically referred as swing options and give their holder the right, but and not the obligation, to acquire a given commodity in predetermined amounts, *n* times during a certain time period, while the minimum and the maximum amounts to be bought during contract's validity are also specified at the same time. The option holder who fails to buy the minimum amount specified has to pay penalties. When those or similar features are embedded in long-term Energy Contracts, investors usually refer to them as *take-or-pay* contracts (Kaminsky, 2012, p. 152).

[5] Disregarding the initial cost / profit that was realised in the moment of the purchase / sale of the option.

As big jet fuel consumers, airlines have a strong incentive to set an upper limit (a cap) for their fuel expenses. This can be achieved by buying sufficient call options to cover for their partial or entire expected fuel consumption within a certain time frame. By doing so, the airline sets the cap for its fuel expenses, while, at the same time, makes sure that it can benefit from an unexpected decrease of the spot fuel prices. The amount of money that needs to be spent for premium however, can be significant, and most of the companies cannot pursue this strategy (Morrell, 2013). Instead, the airlines can engage in simultaneous purchase and a sale of a call and a put option respectively, with the same underlying and maturity. This strategy is often referred to as a *collar*. A special type of a collar structure has been presented in the figure below. It is referred as a costless collar, because the premium paid for the purchase of a call is equal to the one obtained for the sale of a put.

Figure 3: Costless long call / short put collar



Source: Own work.

We can analyse the fine mechanics of a collar arrangement, by presenting the one suitable for jet fuel hedging. In this hypothetical collar arrangement, the airline acquires call options on jet fuel, for a certain premium, setting a price cap for its fuel expenses and matching it with the call's strike price, denoted by K_c on the first plot. At the same time, the same airline issues put options with strike price K_p, lower than the strike of the acquired call. If at the time of maturity, the spot price of the jet fuel happens to be above the strike price: $S_t > K_c$, the call is in the money and the airline company will exercise it which will allow it to pay for the needed fuel less than it would had it not acquired the call option earlier. At the same time, the issued put option will be out of the money, and it will have expired unused. If at the time of maturity the spot price of the jet fuel falls below the put's strike: $S_t < K_p$, the put will be exercised, as the option is on the money for its holder. This means that the airline would not be able to benefit from the lower, market price of jet fuel, as it would have a contractual obligation to pay the strike price K_p. It could well happen that, at the time of maturity, the market price of jet fuel is just between the two strikes: $K_p < S_t < K_c$. In this case, neither of the options is in the money and both will expire unused, so the airliner will pay the market price. The total cost of this entire collar structure is the difference between the premium paid for the call option and the premium received from the sold put. It is, of course, possible to construct the costless collar structure, presented on the third plot of the Figure 3. By altering the number of issued put options or the strike price in them, it is possible for an airline to offset its costs related to call option purchase completely, while, at the same time, having the net costs of jet fuel locked in the range of the lower strike in the put and the upper strike of the call (James, 2008).

2.4 Forward Contracts and how they can be used in jet fuel hedging

Forward Contracts are agreements where one party agrees to buy a commodity at a specific price on a specific future date and the other party agrees to make the sale. Goods are actually delivered under Forward Contracts (Birgham & Houston, 2018). Given that all the details concerning the Contract are negotiated between the participating parties (just like with Swaps and Options), forwards are traded over the counter and not on an Exchange Market[6]. This means that the counterparties bear the entire risk of default until the Contract is terminated. Subsequently, Forward Contracts tend to be used primarily by institutional investors and their most credible clients. Since the Contracts are arranged directly between the interested parties and not through a clearing house, there are no periodic adjustments of respective parties' positions. Forwards are settled at the expiration date, and most often in the form of physical delivery of the asset. (Morrell, 2013).

In the airline industry Forward Contracts can be very useful for the fuel hedging purposes. Every airline should be able to estimate its fuel needs effectively for the foreseeable future. Management teams should be able to use this information, as well as some professional intuition on future fuel prices and negotiate all the details of a Forward Contract with a supplier, according to the company's needs. To illustrate the use of a simple Forward Contract to hedge against fuel price risk, let us assume that an airline initiates a Forward Contract with a local jet fuel supplier present on a location of strategic importance. The airline agrees to buy up front the amount of 100,000 gallons of jet fuel, at \$2.5 per gallon to be delivered to the storage facility of the airline's choosing six months into the future, just at the time when the current stock is expected to be exhausted. Six months later, when the Contract matures, the spot price for jet fuel stands at \$2.9 per gallon. As the spot price is above the contracted price, the airline gains a premium of \$ 0.40 per gallon. Had the company not entered the hedge, it would have paid \$290,000 for this amount of fuel on the

[6] In practice however, most OTC contracts have standardised features, as arranging OTC deals from scratch would produce prohibitively high financial burden. The market participants, therefore, gravitate intentionally towards transactions that represent a trade-off between mitigating certain risks and minimising transaction costs (Kaminsky, 2012, p. 123)

spot market. On the contrary, had the spot price been below the agreed forward price, the airline would have made a loss on the hedge.

Aside from the obvious danger of overpaying for the underlying commodity, there are other, more elusive disadvantages to arranging a forward agreement on jet fuel. Fuel suppliers are experts in the industry; they are probably in a far better position to anticipate future fuel price movements. It is not very likely that a single airline would be able to negotiate particularly good terms of the Contract. Furthermore, entering a Forward Contract without a clearing house that would act as an intermediate exposes both parties to a risk of default, thus introducing credit risk. Moreover, the lack of anonymity in such Contracts, may have strategic disadvantages to both parties. Finally, as there is no compulsory marking to market throughout the life of the Contract, it may be difficult to determine its market value and almost impossible to cancel it prior to its expiry (Berk & DeMarzo, 2017).

2.5 Commodity Futures Contracts and jet fuel hedging

Futures Contracts are legally binding, highly standardised agreements, where counterparties agree to buy or sell an asset at an agreed future date for a predetermined price. The party agreeing to buy an asset and receive delivery has a long position in the Contract, while the party that agrees to sell and make delivery of the asset assumes the short position (Errera & Brown, 2002). Standardisation of Contracts makes it possible for futures to be traded anonymously on an Exchange at a publicly observed market price. This allows buyers or sellers to transfer contract ownership to another party easily by way of trade at any moment, during the life of the Contract. The following details are pre-specified in an Energy Futures Contract (Hull, 2015).

1. Underlying asset (crude oil, for example) on which the Contract is based
2. Contract size: The volume of the underlying asset per single Contract
3. Quality and delivery arrangements: The place where delivery will be made, as well as the detailed commodity quality, must be specified by the exchange
4. Expiration date: The date when the Contract in question expires and all the related obligations terminate

Given this standardisation of the Contracts, the only contract variable is the futures' price. The price is discovered in the process of bidding and offering, also known as quoting, until a match (trade) is made. Some exchanges impose limitations on daily price movements or on the size of positions one can have in any given contract. These limits are aimed at preventing speculators from influencing the market excessively. Trading on an exchange instead of OTC allows participants to reduce the likelihood of default on the contract to a minimum. This credit protection is technically assured by the clearing house associated with the exchange where the trade is organised.

At the moment when a transaction is made, the clearing house is assigned between the original buyer and seller. This is achieved through a novation process, where the clearing house assumes the other side of the two new transactions (Kaminsky 2012, p. 202). The clearing house guarantees the performance of the contracts by requiring each participating party to deposit funds in the amount of a certain percent of the notional value of the Futures Contract at the contract's inception. These funds are placed on a margin account, and it is referred to as the initial margin. The maintenance margin, which is specified for every contract separately following appropriate methodology developed by the Exchange Market, is the minimum amount that needs to be maintained at any given time in the margin account. At the end of every trading day during the Contract's validity, the corresponding margin accounts of the counterparties are credited or debited to reflect the gains and losses from their respective positions in the Contract. Namely, if at the end of the trading day, the futures' price drops, and closes at any value lower than that specified on the Contract's inception, the margin account of the party with the long position is debited by the total amount of the difference between the two mentioned prices multiplied by the size of the party's position. This debited amount is credited to the margin account of the party assuming the short position in the same Contract. The transfer goes in the opposite direction when the futures' price closes above the initially agreed price. This adjustment is called daily settlement or *marking-to-market*, and its purpose is to reflect the present market value of the Contract accurately. When the amount on the margin account falls below the maintenance margin the investor receives a *margin call*, and is asked to top its margin account up, at least to the initial margin level by the end of the next trading day. If the investor does not meet the said requirement, the clearing house may reduce the party's position in accordance with the amount of funds remaining in the margin account, or the position will be liquidated automatically. Conversely, if the amount on the margin account rises above the maintenance margin due to favourable futures' price movements, all the excess balance can be withdrawn. (Errera & Brown, 2002).

There are two important risks associated with hedging jet fuel using Futures Contracts worth pointing out. The business losses are easily offset by the gains on the Futures Contracts, but when the firm starts losing money on its positions on futures, it risks receiving margin calls before it realises cash inflows from the business gains. To be able to maintain the hedge, the firm must be able to provide the cash required to meet its margin requirements, or it may be forced to default on its positions. In fact, this liquidity risk can even put the entire company in danger.[7] Another risk worth mentioning is referred to as the basis risk. It exists whenever the firm's exposures are not correlated perfectly to the value of the Futures Contracts it is using to mitigate them. Reasonable hedging instruments for jet fuel exposure are futures on oil or oil distillates other than jet fuel, as there is a well-developed, liquid and global market for those (Berk & DeMarzo, 2017).

[7] A well-known example is the one of Metallgesellschaft Refining and Marketing (MGRM) that accrued huge losses on its oil futures and went bankrupt in 1993.

As already mentioned, airlines usually use futures on commodities that are closely related to jet fuel, such as crude oil or oil derivatives. This way the airline initiates the practice of *cross hedging*. Since the asset used for hedging differs from jet fuel, the company needs to find a way to decide on the exact number of Futures Contracts it should buy, so that the fuel exposure is offset most effectively. For this, the airline calculates the hedge ratio, as a ratio of the position taken in Futures Contracts to the size of the exposure (Hull, 2015). The optimal hedge ratio is the one that minimises the variance of the value of the entire hedged position. The minimum variance hedge ratio is expressed with the formula below:

$$h* = \rho \frac{\sigma_s}{\sigma_f} \tag{2}$$

where h^* represents the optimal hedge ratio, σ_s and σ_f are Standard Deviations of the spot price change and the futures' price change. while ρ represents the coefficient of correlation between the two.[8] Once the optimal hedge ratio is calculated, the hedger only needs to multiply it by the ratio of the exposure that is being hedged (Q_A), and divide everything by the size of the individual Futures Contract (Q_F), both of which are expressed in the same units of measure:

$$N^* = \frac{h^* Q_A}{Q_F} \tag{3}$$

This gives the total number of Futures Contracts that needs to be purchased for the hedge (N^*).

To conclude the discussion about the forwards and futures, given their similar nature, it is important to point out their differences more explicitly, as it would help one determine which of the two is more appropriate for hedging purposes:

1. Standardisation: Similar to the other OTC Contracts (Swaps and Options), forwards are negotiated privately between two parties. In essence, this means that there are no restrictions regarding variabilities of contractual arrangements that can be nested in a Forward Contract. Futures Contracts on the other hand, are completely standardised with respect to all of their defining features, such as the expiration date, specification of the underlying commodity, contract's size, delivery date and location.
2. Exchange-traded vs. over-the-counter: Given the fact that all of the defining details of a Forward Contract are negotiated privately, they must be arranged and settled OTC. The highly standardised nature of Futures Contracts makes it possible for them to be traded on an Exchange. This allows futures to be traded anonymously, as there is a clearing house within the Exchange that matches two willing parties in a Contract. Since it is not important who exactly is on the either side of a Future

[8]More detailed elaboration of how the optimal hedge ratio is estimated will be presented in the methodological part of this thesis.

Contract, the ownership of the contract is easily transferable. It is possible for any of the parties in a Futures Contract to close their position prior to the Contract's expiration, simply by entering into the opposite trade to the original one, effectively avoiding the final cash settlement and commodity delivery. This is obviously not possible in a Forward Contract.

3. Credit risk: Participants in a Futures Contract are linked to one another through a clearing house, which assures both sides of the Contract are creditworthy through a system of margin accounts which effectively serve as collaterals. On the other hand, no intermediate is needed in a Forward Contract for the Contract to be made, which leaves both sides of the Contract exposed to the risk of the other participant failing to meet the contractual obligations at the Contract's maturity.
4. Marking to market: Daily settlements on either party's margin account is a particularly important difference between Forward and Futures Contracts. With Forward Contracts, a single cash transfer is expected at one point in the future. Therefore, a company must discount this transaction using the appropriate discount rate in order to have the Contract correctly recorded in its Balance Sheet at its Net Present Value (NPV). On the other hand, Futures Contracts are marked to market daily, which assures the exact value of the Contract is known at any given moment and given the fact that they can be converted to cash at the click of a mouse, they are carried in the books as a highly liquid asset. This mechanism, however, presents a serious danger for the company, once it starts receiving frequent margin calls.
5. Market participants: Forward Contracts, being purely OTC Contracts, are in practice only arranged between institutional entities with above average credit ratings. Those are well known industrial firms, hedge funds, investment banks or, in the case of jet fuel hedging, powerful legacy carriers and global fuel suppliers. Futures are accessible on an Exchange and are, therefore, available for retail participants, such as smaller airliners, private jet companies, or any such company which desires to conceal its hedging strategies from its competitors.

3 DATA AND METHODOLOGY

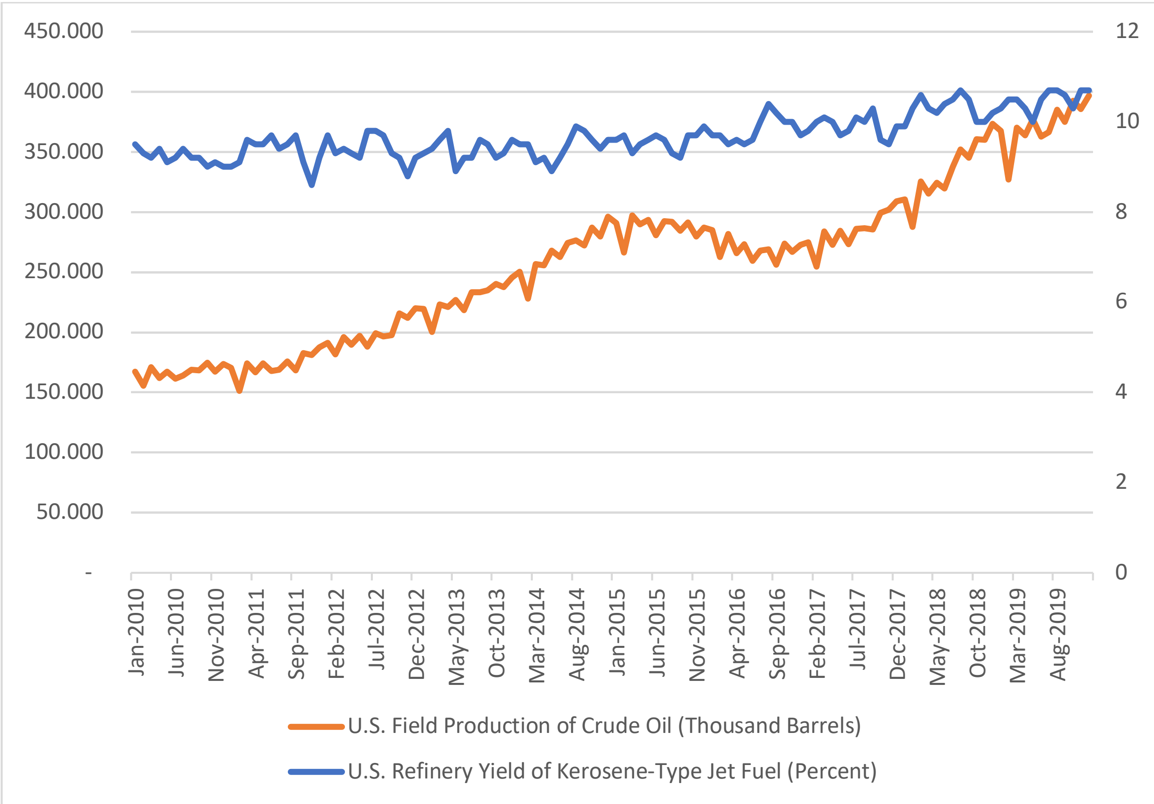
3.1 Jet fuel specifications and recent developments in the crude oil market

Jet fuel is a specialised form of petroleum-based fuel used for powering jet and turbo-propelled engine aircraft. Jet fuels are produced from crude oil using fractional distillation in refineries. This process involves heating crude oil gradually. When the boiling point of a certain component – a "fraction" – of the crude is exceeded, it passes into the gas phase, rises away from the heat source and starts to cool. As the temperature decreases, the fraction turns into liquid once again, and it can be drained from the distillation column easily. Jet fuel belongs to the class of middle distillates, with a boiling point between 175°C and 288°C. When it burns in the jet engine, jet fuel exhaust consists mainly of carbon dioxide, some water vapour, and lots of hot air. Jet A1 and Jet A are primary grades of aviation fuel used in commercial airline industries, and their production is internationally standardised. The main difference between them is a blend of additives that make Jet A1 type sustain a lower freezing point (-47° C). This is particularly important for airports that experience extremely cold weather, and for airlines that plan long hauls and high-altitude flights, as the fuel stored in wings can reach nearly freezing temperatures.

The airline industry is capital-intensive, and the effects of the investments in it are long lasting and synergetic. Jet fuel production, as one of its parts, is characterised by significant economies of scale, which makes good foundations for an ever-expanding global market. This abundant supply, is on the other hand met by a strong growth in demand, coming from the rapid worldwide growth in commercial passenger transport. The IATA Report on expected increase in passenger count on a global scale from 2015, predicted a strong growth for the period of 2014 – 2034, particularly in the Chinese market, which is expected to overtake the US as the largest domestic market. In fact, the global increase in the number or air travellers is expected to be mainly due to the Asia Pacific region, which is expected to grow by approximately 4.9% per year, reaching 1.753 billion passengers a year by 2034 (IATA, 2015).

The time period covered in this thesis is marked by a shift in global oil supply. Namely, the US had been intensifying their research and investments in oil extraction from their massive shale deposits from the early 2000s. The particular technology that was perfected – a combination of horizontal drilling and hydraulic fracturing, coupled with growing oil and gas prices after the crisis of 2008, provided positive incentives for companies to invest in new facilities and manpower, subsequently increasing the amount of oil produced in the US available for world's market substantially (Brown & Yucel, 2013). In fact, the US was producing 9 million barrels of crude oil per day in 2014, which is a tremendous increase from just over 5 million barrels per day in 2006 (Bordoff & Houser, 2015). Afraid of losing their market share, OPEC decided not to decrease their production quotas the very same year (Reed, 2014). This additional oil supply was feeding the market gradually from 2010. onwards, but it was not until late 2015 that the global market started experiencing significant increase in crude oil supply as a direct consequence of the US congress' decision to lift a 40-year-old ban of crude oil export (Wingfield, 2015). The considerable increase in crude oil supply that followed, was not met by a sufficient demand, and the price of oil fell throughout 2015, but rebounded rather quickly as a consequence of the increased global demand that followed. The US, as it is apparent in the graph below, maintained and increased high levels of oil and gas production, and as a result, overcame both Saudi Arabia and Russia as the world's biggest oil and gas producer respectively (Yergin, 2015).

Figure 4: US Crude Oil production and its refinery yield of Kerosene – Type jet fuel



Adapted from EIA (2020a).

The fact that the share of crude oil refined into kerosene in this period remained relatively stable in the US and Europe[9], implies that the correlation of price movements between those two commodities on a year-to-year basis, - should remain stable and high. This high correlation in price movements between the two commodities makes crude oil a good candidate for jet fuel hedging practices. The literature on the subject of cross hedging, suggests using commodities that share many key features with the one being hedged. For that reason, in this thesis, I consider heating oil, traded in the US and gasoil, available in Europe. These two products are extracted on the same stage of oil refinement as jet fuel and using the same technology, so any advancements in the actual technology of refinement which could have influenced prices of either of the two commodities, would, necessarily, also have influenced the jet fuel price.

[9] The report and datebase can be accessed on the following link: https://ec.europa.eu/eurostat/statistics-explained/index.php/Oil_and_petroleum_products_-_a_statistical_overview#Use_of_petroleum_products

3.2 Data specification

In the analysis that follows, I will be using information on price movements of jet fuel on one hand, and crude oil and oil derivatives on the other. As I am interested in the potential differences that jet fuel hedgers might need to consider in the US as opposed to the European market, I will be using appropriate commodities that are traded on each of the markets. All of the prices were retrieved in from the Bloomberg terminal.

Jet Fuel Colonial Grade 54 (JP54) is the type of fuel that serves as the jet fuel price reference for the US market in this thesis. This grade of fuel originates from the crude oil extracted and refined in the US Gulf Coast area, and it is available for delivery at many terminals along the US East coast along the Colonial pipeline. The said pipeline passes through the biggest conurbations on the US East coast. This makes it very convenient for the local wholesale and retail companies to serve all the major airports in the area. Information on crude oil price movements will be incorporated in the further analysis through the pricing of New York Mercantile Exchange (NYMEX) traded futures on West Texas Intermediate (WTI). WTI is a US blend of several streams of domestic light sweet crude oil. The delivery point is in the vibrant trading hub of Cushing, Oklahoma, and the futures are based on 1,000 barrels per contract, priced in US dollars and cents per barrel. The maturities of the chosen futures are 3, 6, and 12 months, starting from January 2015. and ending with the December delivery in 2019. Futures on heating oil will be used in the analysis for the US market. Heating oil is a low-viscosity fuel derivative, used mainly for heating of residences and businesses in the US North-East. It is separated from the crude at about the same stage as the jet fuel, which is why it is considered to be a valid hedging commodity, given that the improvements in its production, storage and transportation are likely to influence price movements of jet fuel itself. The NYMEX trade of heating oil is organised through NY Harbour ULSD (Ultra Low Sulphur Diesel) Futures Contracts, which are quoted in US dollars and cents with the Contract size of 42,000 gallons (1,000 US barrels) and the physical delivery is in New York harbour. In this thesis, I used Contracts with 3, 6 and 12-month maturities, from January 2015 – December 2019.

For the jet fuel reference price for the European market, I chose the Jet fuel FOB ARA Index, which consists of the quotes for jet fuel stored on barges and ready for immediate delivery at any of the tankering ports in the Antwerp-Rotterdam-Amsterdam region. The quotes are available on the Bloomberg terminal under *JET1NEFB* code. Crude oil prices for the European market are those of the Brent crude oil futures, traded on the London based, Intercontinental Exchange's (ICE) division - ICE Futures Europe. The underlying commodity for these futures is a blend of the North Sea crudes, originating from the offshore extraction sites within the UK and Norway's territorial waters. Ever since the oil discovery and beginning of extraction in this region in the 70's and 80's, North Sea region offered stable governments, good access to markets and significant financing opportunities, which all led to Brent developing itself into a benchmark, widely accepted by the European, Russian, North and West African producers as well as some producers in Asia. The Brent oil futures that are used in this analysis are physically deliverable in Sullom Voe, the United Kingdom, with the Contract size of 1,000 barrels, originally priced in US dollars and cents, although I used the Bloomberg quotes recalculated to Euros. Gasoil is a name used in the European Energy Market for the same oil distillate that is known as heating oil in the US. Europeans, however, do not use this product for heating spaces in winter at all. In fact, the oil derivative that is used by far the most in homes/water heating and cooking in the EU is natural gas (Eurostat, 2020). Recognising the importance of having an instrument suitable for forward trading of gasoil, the ICE has created Low Sulphur Gasoil Futures Contracts. Hedgers and speculators alike can therefore trade the commodity conveniently. Contract's size is 100 metric tonnes of gasoil, with the delivery at any of the ports in Antwerp, Rotterdam, Amsterdam, Flushing and the Ghent region. In the analysis, just like with the other instruments, I retrieved daily quotes from the Bloomberg terminal on Contracts with 3, 6 and 12-month maturities, from January 2015 – December 2019.

Table 1: Financial derivatives used for cross hedge calculations

Futures Contract	Symbol	Trading Venue	Size of a single Contract	Delivery place
WTI Crude Oil	CL	NYMEX	1,000 barrels	Cushing, Oklahoma
NY Harbor ULSD	HO	NYMEX	42,000 gallons	New York harbour, New York City
Brent Crude	CO	ICE	1,000 barrels	Sullen Voe, Scotland
Low Sulphur Gasoil	QS	ICE	100 metric tonnes	Any port in the ARA region

Source: Own work.

The Table below gives a general impression on how closely related price movements of crudes and derivatives really are. I have calculated the correlation coefficients of daily price movements for the US and European market separately, in line with the general idea of providing information and calculations for each of the markets appropriately.

Table 2: Correlation coefficients between daily closing quotes (period of 2015-2019.)

	Jet fuel 54		ARA jet fuel
WTI Crude Oil	0.9245	Brent Crude	0.9753
Heating Oil	0.9866	Gasoil	0.9922

Source: Own work.

The calculated correlation coefficients are all close to 1, with oil distillates exhibiting almost perfect correlation for both the US and European markets.

3.3 Methodology

Airline companies need jet fuel for their operations. As they are not producing any jet fuel themselves and, therefore, not having any control of its future price, they are constantly exposed to jet fuel's rising future prices. Airlines' hedging practices are, therefore, directed towards offsetting this future rise in fuel prices, and the way to do this is to buy ahead and at known prices, any commodity whose price evolves similarly to that of jet fuel. The way this is analysed in this thesis is through cross hedging by Futures Contracts on crude oil and oil derivatives. This practice is referred to as a long hedge.

Assuming an airline company wishes to protect its future jet fuel acquisition costs from rising prices, it would enter into a term arrangement of buying a certain amount of oil or oil distillate using Futures Contracts. When the Contract reaches maturity and the spot price of the underlying commodity on the open market is higher than that specified by the Futures Contract, the airline can liquidate its open position by shorting the exact same number of Futures Contracts. In this way, the airliner profits from the positive price difference, because the price of futures converges to the commodity's spot price at the time of delivery. If, close to maturity, it becomes apparent that the contracted commodity will be trading at a discount by the Contract's expiry, the airline company can liquidate its position and avoid significant losses that would occur with any later liquidation. It is the specific features of a Futures Contract that allow a hedger to arrange this whole operation.

The idea with this construction is to use the gains in the futures liquidation to alleviate the rising costs of the jet fuel. The particular benefit of hedging with a Futures Contract is that there are no upfront costs, regardless of the size of one's position, except of course for those costs related to daily settlements. Clearly, for such a hedge to be successful, the price of the underlying commodity needs to be consistently highly correlated to the price of jet fuel – only then will the higher jet fuel costs be matched with the higher oil commodity price. Finally, as the futures are predetermined in size, it is very important to determine the optimal number of futures that have to be purchased to hedge the desired amount of jet fuel effectively. The optimal hedge ratio is what helps a company determine how many Futures Contracts it needs to buy so that its risk is mitigated.

As explained in L. Johnson's seminal paper, the return on the portfolio of a hedger who is short on a product, and buys the futures, can be modelled in the following way (Johnson, 1960): Let S_t and F_t represent logs of the spot price of petroleum commodity futures and jet fuel respectively, then the return of the hedger's portfolio R_t is:

$$R_t = \beta\Delta F_t - \Delta S_t \tag{4}$$

where β is the ratio of the number of Futures Contracts needed to hedge the determined amount of jet fuel. This ratio is time invariant and independent of the Contract size. The jet fuel spot price change is captured by ΔS_t, whereas ΔF_t represents the rate of change of the futures' price. Being a linear combination of the two random variables (S_t and F_t), R_t is itself a random variable, which means that its variance can be expressed as follows:

$$V(R) = \beta^2 V(F) + V(S) - 2\beta COV(S,F) \tag{5}$$

where V(R) denotes the variance of the portfolio R_t; V(S) denotes the variance of the change of jet fuel spot price ΔS_t: V(F) denotes the variance of the change in futures' prices ΔF_t and COV(S, F) represents the covariance of ΔS_t and ΔF_t respectively. The number of Futures Contracts that minimise the total portfolio variance, i.e. optimal hedge ratio, is obtained by taking the first derivative of equation (5) with respect to β and setting it to zero:

$$\frac{dV(Rt)}{d\beta} = 2\beta V(F) - 2COV(S,F) = 0 \tag{6}$$

Now we check the second order condition to see that *β* indeed gives the minimum value of the portfolio variance:

$$\frac{d^2 \mathrm{V(Rt)}}{d^2 \beta} = 2V(F) > 0 \tag{7}$$

From equation (6) we can express *β* in the following way:

$$\beta = \frac{\mathrm{COV(S,F)}}{V(F)} \tag{7}$$

Since the coefficient of correlation between price movements of jet fuel (spot market) and the Futures Contracts can be expressed as $\rho = \frac{COV(S,F)}{\sqrt{V(S)}\sqrt{V(F)}}$, then we can express the optimal hedge ratio *β**, as:

$$\beta^* = \frac{\sqrt{\mathrm{V(S)}}}{\sqrt{V(F)}} \rho \tag{8}$$

With historical data in hand, this effectively means that *β** can be estimated (Ederington, 1979) (Hull, 2015). In this study, I will use Ordinary Least Squares (OLS) and Error Correction Model (ECM) for the purpose.

3.3.1 Ordinary Least Squares

Any of the series of data that I am using in this thesis is a single realisation of a stochastic process. This randomness in realisation of each of the processes allows us to use the same concept of OLS estimation in the analysis as one would use in cross-sectional data, where estimation is conducted on a random sample from the whole population. In order to use the findings of the subsequent analysis properly, I will present the Gauss – Markov assumptions in time series regressions (Wooldridge, 2013). Proofs and in-depth theoretical explanations of each of the assumptions and their violations are far beyond the scope of this thesis and are therefore omitted.

1. Assumption: The model being estimated is linear in its parameters. The general form of such model is:

$$Y_t = \beta_0 + \beta_1 X_{t1} + \dots + \beta_k X_{tk} + u_t \tag{9}$$

Where $Y, X_1, \dots X_k$ represent stochastic processes and the variable Y is contemporaneously affected by the linear combination of the explanatory variables $X_1, \dots X_k$ and a sequence of error disturbances u_t, with $t = 1, \dots n$ representing the number of observations (time periods). Parameters $\beta_0, \dots \beta_k$ are unknown, and they are to be estimated.

2. Assumption: There is no perfect collinearity in the explanatory variables.
3. Assumption: The conditional mean of the error term in the model is zero for all time periods:

$$E(u_t|X) = 0,\ t = 1, 2, \dots n \tag{10}$$

The equation above implies that the error terms and the explanatory variables are contemporaneously uncorrelated. When the above 3 assumptions are satisfied, OLS estimators are unbiased (Wooldridge, 2013, p. 352).

4. Assumption: Error terms u_t are homoscedastic – $Var(u_t|X)$ does not depend on X and $Var(u_t)$ is time invariant.
5. Assumption: No serial correlation in the error terms:

$$Corr(u_t, u_s) = 0, \text{ for all } t \neq s \tag{11}$$

When all 5 assumptions listed above are satisfied, under the Gauss – Markov theorem, the OLS provides the best linear unbiased estimators (Wooldridge, 2013, p. 354).

6. Assumption 6: Error terms are independently and identically, normally distributed:

$$u_t \sim N(0, \sigma^2) \tag{12}$$

The validity of this assumption is not imperative for the accuracy of the estimators, but it is crucial for statistical inference and calculations of confidence intervals. The stationarity of the time series used in linear regressions is another important concept that must be accounted for, and I dedicated a significant portion of the next chapter to it.

In order to estimate the optimal hedge ratio and, finally, determine which commodity would provide the most effective hedge for jet fuel prices on our data sample, I am interested in the way the prices of jet fuel and each of the commodity futures change over time. This can be presented with a simple, static model, with the regressand being a time series of daily spot quotes of jet fuel (S_t), and daily closing quotes of a Futures Contract (F_t) as a sole regressor:

$$S_t = \alpha + \beta F_t + u_t \tag{13}$$

Where u_t is assumed to be serially uncorrelated, homoscedastic and an i.i.d. error term. However, it is important to account for the fact, that the data in levels might not be stationary. To circumvent the issue of spurious regression, I will in fact estimate a slightly different model from the one presented by equation 13.

$$\Delta lnS_t = \alpha + \beta \Delta lnF_t + u_t \tag{14}$$

Log - differences of the original series make data suitable for the OLS estimation, and now the variables are day-to-day growth rates. OLS estimation of equation (14) will give us the slope estimate β^*, such that the returns of a portfolio consisting of the commodity to be hedged (S_t – jet fuel) and the instrument (F_t - future), have minimum variance (Ederington, 1979). Given the fact that the time series in our analysis are cointegrated, which is proven further in the text, OLS is, purely technically speaking, not the optimal method of estimation. For that reason, the optimal hedge ratio β^* will also be estimated using the Error Correction Model (ECM).

3.3.2 Error Correction Model

ECM should be used whenever we can prove cointegration between the series. Cleverly including a new regressor in the equation for estimation would give more explanatory power to the model, by specifying the way a long run relationship between two variables is re-established after a short-term shock. In our particular case, cointegration could be expected, because both series are non-stationary in levels (as is shown in the next section), and it is expected that in the long run they move similarly since they belong to the same group of products. The oscillations in supply/demand of oil for example, are expected to influence the prices of jet fuel and any of the oil derivatives I chose to use for this analysis, in the same way. In general, the ECM equation is specified as follows:

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \beta_2 \varepsilon_{t-1} + u_t \tag{15}$$

where ε_{t-1} represents the cointegration term and has the form of $\varepsilon_{t-1} = S_{t-1} - \gamma F_{t-1}$. It is, however, possible and recommended to estimate an augmented model. Namely, lagged differences of the spot jet fuel and derivative prices should be included, where the number of lags is determined by the Akaike Information Criterion (AIC). Finally, the form of ECM to be estimated is:

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \beta_2\, \varepsilon_{t-1} + \sum_{k=1}^{K} \gamma_k \Delta\, S_{t-k} + \sum_{l=1}^{L} \delta_l\, \Delta\, F_{t-l} + u_t \quad (16)$$

The term cointegration represents the response to a disruption of the long-term co-movement of the two series (The Royal Swedish Academy of Sciences, 2003). More intuitively, the equation models the way how long-term co-movement is re-established once the market shock has happened. For that reason, the cointegration term is lagged for one period. Coefficient β_2 can, therefore, be interpreted as the speed of adjustment to the long run cointegration and it measures the amount of correction made. As for the optimal hedge ratio that we are in fact most interested in, it is still the estimate of the parameter by the futures' quotes (β_1^*). The idea is that, by introducing the additional regressor we obtain a more precise estimate for the optimal hedge ratio.

3.3.3 Measuring hedge effectiveness

To determine hedge effectiveness for each of the models, I will use the measure developed by Juhl et al (Juhl, Kawaller, & Koch, 2012). It is appropriately called *R^2 analogue*, as it also evaluates the explanatory power of the model. The formula is given below:

$$R^2\ analogue = 1 - \frac{SSE}{SST} \quad (17)$$

where *SSE* represents the total variation in the time series:

$$SSE = \sum (\Delta S_t - \beta^* \Delta F_t)^2 \quad (18)$$

where β^* represents the estimated hedge ratio for each of the models. SST represents the total variation in the time series about their means:

$$SST = \sum (\Delta S_t - mean(\Delta S_t))^2 \quad (19)$$

Determining the effectiveness of a hedge is important to the company's accountants and not only its Risk Management Department. Due to different ways, the *fair value* of the financial instruments used for hedging and the *fair value* of the assets that are being hedged should be registered in Financial Reports, as an accounting mismatch can trigger a rise in volatility in the Income Statement. Hedge accounting was developed specifically to solve this issue, and a company can use it only if it proves that the hedging programme (active at the time that is covered by the specific Report) is „very effective". There are different ways of proving that the hedge has been effective, and the common one that involves a quantitative method is a regression that determines the correlation between the fair values of the hedging instrument and that of the hedged asset, by analysing the slope of the regression line (optimal hedge ratio) and the coefficient of correlation (R^2). Highly effective hedges are those with slope parameter values are within a range of – 0.8 and 1.25 and $R^2 > 0.8$ (KPMG, 2015).

4 TESTING AND RESULTS

4.1 The concept of stationarity

In order to estimate a linear model accurately, it is important to use a time series whose statistical properties do not depend on the time at which the series is observed. It should be intuitively clear that time series which exhibit features that are time varying misrepresent the stochastic processes that generate them. In turn, this leads us to the conclusion that the estimators obtained from non-stationary data should not be used. In fact, the idea of spurious regressions pointed out in the seminal paper published in the mid-seventies, transformed the way econometricians model economic time series relations (Granger & Newbold, 1974). For the purpose of completeness, I will introduce the proper definition of the term and try to explain how it translates to the process of estimation with real data.

A time series is said to be (weakly) stationary if its mean and variance are constant and finite over time, while its covariance can be a function of a number of lags between observations but must not be the function of time (Hayashi, 2000). More precisely, for the time series y_t:

$$E[y_t] = \mu \quad \wedge \quad |\mu| < \infty \tag{20}$$

$$V(y_t) = E\,[(y_t - \mu)^2] = \sigma^2 \;\wedge\; \sigma^2 < \infty \tag{21}$$

$$COV(y_t,\, y_{t+k}) = COV(y_t,\, y_{t-k}) = \gamma_k \;\wedge\; \gamma_k < \infty \tag{22}$$

The proven stationarity in the data allows us to use a sample path to characterise the entire distribution of a process from where the time series originates. In addition to stationarity, we assume weak dependency of the data: y_t and y_{t-h} are approximately independent for $h \to \infty$. This means that each new observation contains new information about the distribution. Under the fulfilled assumptions of weak stationarity and weak dependency, the sample average $\overline{y_t}$ will converges to the unconditional expectation $E(y_t)$ – the mean of the process. Also, the same assumptions replace the i.i.d. assumption in the case of cross-sectional data, in the way that weak dependency replaces independency and weak stationarity implies that the data points are drawn from the same distribution. That together means, that OLS linear regression can be used in the estimation.

Using non-stationary data in OLS linear regression would lead to spurious regression, one that appears to fit the model well, but is actually worthless. In the case of stationary data, unexpected and severe shocks that move the system from its long-run mean have weaker and weaker effects for the data points being more away from the actual shock. However, with the non-stationary data, the persistence of shocks can be infinite (Hayashi, 2000). Finally, one cannot use hypothesis testing on the estimates, as the distributions are miss-specified.

To test for stationarity in my data, I conducted two types of tests in this thesis: The Augmented Dickey – Fuller test (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. ADF is the test used most commonly for determining the stationarity of a time series. In fact, it tests for non-stationarity, as its null hypothesis assumes the time series contains a unit root. One important thing to note is that ADF relies on the same logic as the Dickey – Fuller test (Dickey & Fuller, 1979), with a difference that now we assume that the data generating process has some higher order autoregressive moving average dynamics ARMA(*p,q*) that can be approximated with an AR(*p*) model, and our goal is to determine how much the present value of a variable is dependent on its previous values. Any textbook on Econometrics includes a more or less mathematically rigorous chapter dedicated to derivations of the Dickey – Fuller tests statistics (Hamilton, 1994). Without going into detail, I will therefore only present the logic of the test, while stressing some points, useful for work with real data. Let us consider an AR(1) representation of a time series y:

$$y_t = \varphi\, y_{t-1} + \varepsilon_t \tag{23}$$

where ε_t represents so-called white noise process with data points being i.i.d. and $\varepsilon_t \sim N(0, \sigma^2)$. It can easily be shown that the autoregressive process presented in the equation (23) does not satisfy conditions of weak stationarity when $\varphi = 1$. We cannot run the OLS to determine if φ is statistically different from 0, as under the null, test statistics from such a regression have non-standard distribution, so the inference would be inappropriate. The way to test this is indirect. We take the first difference from both sides of the equation (23) to obtain:

$$\Delta y_t = \beta y_{t-1} + \varepsilon_t \tag{23}$$

where $\Delta y_t = y_t - y_{t-1}$ and $\beta = \varphi - 1$, and test the hypothesis:

H_o: $\beta = 0$ (equivalent to $\varphi = 1$)
H_1: $\beta < 0$ (equivalent to $\varphi < 1$)

This two-step process is referred to as a Dickey – Fuller testing procedure (DF) (Dickey & Fuller, 1979). Cases where $\varphi > 1$ are theoretical and are not considered in practice. If we wish to include more lags in the starting equation (23), the subsequent testing is referred to as an Augmented Dickey Fuller test (ADF). We can use the Akaike Information Criterion (AIC) or Bayesian Information Criteria (BIC) to determine how many lags to consider. Although some of the most relevant textbooks on time series analysis identify four cases, or types of model specification for DF testing (Hamilton, 1994), in practice we usually consider three of them, depending on the inclusion of the constant term and the trend:

Case 1: No constant and no trend	$\Delta y_t = \beta_1 y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-I} + \varepsilon_t$
Case 2: Constant and no trend	$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-I} + \varepsilon_t$
Case 3: Constant with a trend	$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_3 t + \sum_{i=1}^{p} \gamma_i \Delta y_{t-I} + \varepsilon_t$

It is very important to choose the right specification of the test because the critical values differ with the type of test being used and the number of observations in hand. Although used most commonly, the ADF test is known to have at least two weak points (Paparoditis & Politis, 2016):

1. In case the chosen number of lags is too small, the remaining autocorrelation in the ε_t is likely to bias the estimate.
2. Choosing a number of lags that is too big, on the other hand, creates a problem in the power of the test. Namely, the test is poor in distinguishing if the process is stationary, when the estimate is close to the boundary value

It is a good practice, therefore, to run another test and confirm the findings. The KPSS test will not be presented in detail here, but I believe it is a good choice, since it actually tests stationarity - only by rejecting H_o can one claim that the process is most likely to be non-stationary (Kwiatkowski, Phillips, Schmidt, & Shin, 1992).

4.1.2 Stationarity testing

The data I used in this research, are time series of daily, closing quotes for Commodity Futures Contracts with 3, 6 and 12-month maturities, with the data series starting always from the 1st trading day in a given year. Series are organised as continuous, rolling contracts - every year's data consists of four 3 - month contracts, two 6 – month contracts and one 12 – month contract series. The series of data are linked, making a continuous series in a way that the last trading day of one Futures Contract is followed by the first subsequent trading day's closing quote of the Futures Contract that will be maturing in three months (or 6 and 12 months, depending on the series). As already explained, due to the specific, non-parametric distributions for both ADF and KPSS test statistics, it is very important to choose the right type of test, since the critical values for either of the tests are different. A good rule of thumb when working with real data is to observe the plot of the data sequence, and, based on the look of the graph, decide what the most appropriate test specification is. On the Figure below, we can see what the plot of a continuous series of three-month WTI Futures Contracts looks like[10]:

[10] Plotted series of quotes of all of the derivatives used in this thesis, for three, six and twelve months of maturity are available in the Appendices.

Figure 5: Daily three-month WTI Futures Contracts closing quotes

Source: Own work.

We can spot several important details in this graph. Two distinct periods can be identified: From 2015 – 2016 and from early 2016 – 2019. As the crude oil price rebounded in the first quarter of 2016, the downward trend was replaced by a profound, much longer lasting, upward trend. Lastly, it is obvious that the regression line would cross the Y axis above the origin. These are all valid arguments to opt for the ADF test as specified by *Case 3*, which includes both a constant term and the trend. The *Jupyter Notebook* programming environment offers both ADF and KPSS tests as functions that can be imported through the *statsmodels* module, where it is easy to specify inclusion of both constant and trend components. Both tests are one-sided but their H_0 are opposite: ADF tests for the existence of a unit root, whereas KPSS tests the non-existence of the unit root. Results of both of the tests of the data in levels are presented in the Table below:

Table 3: Stationarity test results for the US data sample – in levels

		Jet fuel 54	WTI Crude Oil			NY Harbor ULSD			Critical values:	
ADF test		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month	Case 3	
	test statistic	-2.534	-2.637	-2.656	-2.845	-2.289	-2.255	-2.397	1%	-3.966
	p value	0.311	0.263	0.255	0.181	0.439	0.458	0.381	5%	-3.414
	legs used	1	5	1	5	13	1	1	10%	-3.129
	# observations	1230	1226	1230	1226	1218	1230	1230		
KPSS test		Jet fuel 54	WTI Crude Oil			NY Harbor ULSD			Critical values	
		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month	1%	0.216
	test statistic	0.534	0.343	0.347	0.380	0.480	0.473	0.516	5%	0.146
	p value	0.01	0.01	0.01	0.01	0.01	0.01	0.01	10%	0.119

Source: Own work.

Table 4: Stationarity test results for the European data sample – in levels

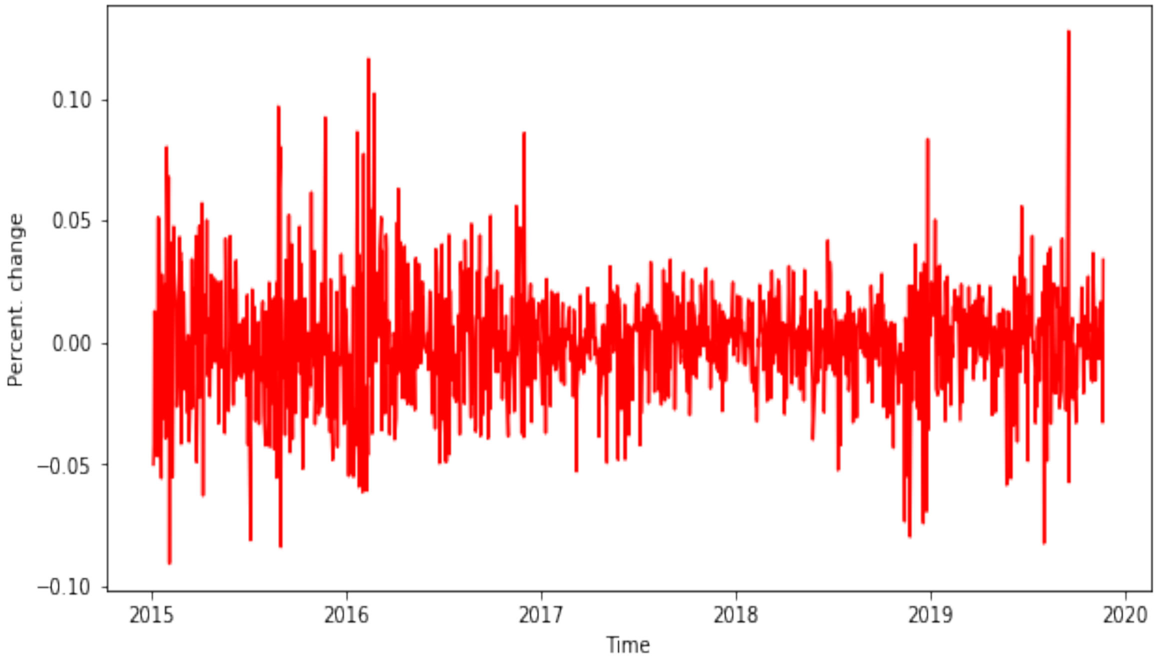
		ARA Jet fuel	Brent crude			Gasoil			Critical values:	
ADF test		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month	Case 3	
	test statistic	-2.347	-2.311	-2.331	-2.365	-2.249	-2.312	-2.375	1%	-3.966
	p value	0.408	0.428	0.417	0.398	0.462	0.427	0.392	5%	-3.414
	legs used	0	1	1	1	0	0	0	10%	-3.129
	# observations	1246	1245	1245	1245	1.246	1.246	1.246		
KPSS test		ARA Jet fuel	Brent crude			Gasoil			Critical values	
		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month	1%	0.216
	test statistic	0.488	0.382	0.392	0.440	0.501	0.506	0.559	5%	0.146
	p value	0.01	0.01	0.01	0.01	0.01	0.01	0.01	10%	0.119

Source: Own work.

As *Tables 3 and 4* show, we are unable to reject the hypothesis of the series being non-stationary, even at the least restrictive confidence level. The KPSS test results are supporting this claim, as the null was rejected easily in every tested series. This means that our data in levels are not suitable for regressions, and they need to be transformed. Taking log - differences[11] is an appropriate choice in this case, as the log transformation penalises excessive variations in level data, while taking first differences eliminates the time dependency between the data points, which means that no trend component should remain. After this transformation, we should observe the plot and decide on the new stationarity test type.

[11] Log transformation in this case means taking natural logarithm *ln()* of each of the data points in the series. It can easily be proven that, by using natural logarithms and when the change of a variable in the consecutives in our data are relatively small, we can consider log-differenced data as a good approximation for percentage growth rates.

Figure 6: Log-differenced three-month WTI Futures Contracts closing quotes



Source: Own work.

Observing the plot of percentage change in growth rates we can see that there is no trend in the series, and it seems that all the values oscillate around 0. This also means that no constant term and no trend component should be included in the stationarity test specification – *Case 1*. In the Tables below I present the results of the second stationarity testing:

Table 5: Stationarity test results – transformed data

		Jet fuel 54	WTI Crude Oil			NY Harbor ULSD			Critical values: Case 1	
ADF test		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month		
	test statistic	-37801	-14.797	-21.498	-21.371	-38.772	-37.839	-37.679	1%	-2.568
	p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	5%	-1.941
	legs used	0	4	2	2	0	0	0	10%	-1.617
	# observation	1230	1226	1228	1228	1230	1230	1230		
KPSS test		Jet fuel 54	WTI Crude Oil			NY Harbor ULSD			Critical values	
		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month	1%	0.739
	test statistic	0.094	0.049	0.055	0.067	0.078	0.082	0.093	5%	0.463
	p value	0.1	0.1	0.1	0.1	0.1	0.1	0.1	10%	0.347
		ARA Jet fuel	Brent crude			Gasoil			Critical values: Case 3	
ADF test		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month		
	test statistic	-35451	-38.695	-38.986	-38.961	-34.899	-34.679	-34.810	1%	-2.568
	p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	5%	-1.941
	legs used	0	0	0	0	0	0	0	10%	-1.617
	# observation	1245	1245	1245	1245	1.245	1.245	1.245		
KPSS test		ARA Jet fuel	Brent crude			Gasoil			Critical values	
		(spot)	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month	1%	0.739
	test statistic	0.071	0.052	0.058	0.067	0.061	0.067	0.078	5%	0.463
	p value	0.1	0.1	0.1	0.1	0.1	0.1	0.1	10%	0.347

Source: Own work.

As we can see in the Tables, all of the ADF tests rejected the null, and none of the KPSS rejected it, implying that the time series show stationary behaviour. With data displaying such characteristics, I can now proceed to OLS regressions.

4.2 Estimating the optimal hedge ratio using OLS

Now that all the data have been prepared, the estimation can be conducted. As is explained in the previous chapter, the transformed data can be thought of as growth rates in percent. By regressing the jet fuel growth rates on each of the rolling futures series, we are determining the slope of the regression line, which is indeed the optimal hedge ratio that we are looking for at this stage of the analysis. The results are presented in the Table below, where all the slope coefficients are statistically significant.

Table 6: OLS estimation results – US market

		WTI Crude Oil			NY Harbor ULSD		
		3 - month	6 - month	12 - month	3 - month	6 - month	12 - month
OLS estimation	constant est.	~ 0	~ 0	~ 0	~ 0	~ 0	~ 0
	p value	1.00	0.96	0.87	0.99	0.99	0.89
	slope est.	0.756	0.791	0.832	0.999	1.06	1.06
	p value	0.00	0.00	0.00	0.00	0.00	0.00
	R-squared	0.615	0.621	0.612	0.827	0.781	0.731
	Dep. Variable:	Jet fuel 54					

Source: Own work.

Table 7: OLS estimation results – European market

		Brent crude			Gasoil		
		3 - month	6 - month	12 - month	3 - month	6 - month	12 - month
OLS estimation	constant est.	~ 0	~ 0	~ 0	~ 0	~ 0	~ 0
	p value	0.91	0.86	0.81	0.97	0.92	0.82
	slope est.	0.572	0.575	0.578	0.907	0.881	0.897
	p value	0.00	0.00	0.00	0.00	0.00	0.00
	R-squared	0.447	0.433	0.405	0.789	0.705	0.683
	Dep. Variable:	ARA Jet fuel					

Source: Own work.

As explained before, the point of our interest is the estimate of the slope, as it is the proxy for the optimal hedging ratio. Our results show that in the case of both US and European markets, the constant term is not much different from zero, and it can be disregarded in any future OLS estimations. The slope coefficients in all of the regressions are statistically significant and have positive signs, which was anticipated. A somewhat surprising result is the coefficient of determination (R^2), that is below 0.8 in almost every case. This is probably due to two significant price drops at the beginning of 2016 and the end of 2018. The results on the US market data indicate that the futures on heating oil fit the model more effectively, compared to the WTI futures. In fact, heating oil futures with the shortest maturity provide by far the highest coefficient of determination, compared to any of the estimated models. As the maturity of the heating-oil Futures Contracts increased, the percentage of the explained variations in the dependent variable decreased. This, on the other hand, is not the case with the futures on WTI, where the coefficient of determination remained stable and just over 0.6 for all the maturities. Results derived from the European markets, however, indicate significantly less explanatory power in the model that uses futures on Brent oil. In fact, the coefficient of determination was consistently below 0.5 in every one of the conducted regressions. On the other hand, it seems like as if the gasoil futures provide a relatively good fit to the model, with higher R^2 numbers, and with the effectiveness of the model decreasing with the increase of the maturities of the used futures. This coincides with the results obtained from the futures on heating oil in the US markets. Although the results at this stage speak strongly in favour of the futures on oil derivatives, the optimal hedging instrument will be determined at the end of the analysis, by comparing the *R^2 analogue* as explained previously.

4.3 Estimating the optimal hedge ratio using ECM

As jet fuel prices were regressed on the futures prices of another oil derivative and given that both of these series are most likely integrated in levels, which was shown by the ADF and KPSS tests, it is possible that the series are in fact cointegrated. This means that, even though those individual series move in a non-stationary fashion individually, deviating constantly from their respective long run means that they do this in a very similar, coordinated way. In fact, a linear combination of the two may exist, that is stationary.

Cointegration testing is relevant in our case, because if we manage to prove a cointegrating relationship between the series, then running OLS regressions on the log-difference stationary series produces suboptimal estimates. This is because the estimating equation we used in the OLS estimation does not include an additional explanatory variable. This variable models the long-term relationship between dependent and independent variables and including them into the estimating equation would necessarily change the values of the estimates. We could say that OLS regression of log-differenced series only models the short-term relationship between the variables. The way around this is to account for the long run co-movement and estimate their relation using Error Correction Model (ECM). For this purpose, I conducted the classical two step procedure as developed by the pioneers in the field of Cointegration, Granger and Engle (1987). It is worth pointing out that this way of building and estimating an ECM is suitable only when we are considering cointegration between two time series. If the number of series is greater, one would need to consider estimating the Vector Error Correction Model (VECM), as proposed by Johansen, another famous contributor to the subject (Johansen, 1995).

The idea behind the concept is presented below for practitioners' reference. Let us consider a simple model, where y_t and x_t are both $I(1)$ series.

$$y_t = \mu + \beta x_t + u_t \tag{24}$$

In equation (24), u_t can be interpreted as some deviation from the long run relationship between the two variables. If y_t and x_t are indeed cointegrated, then the deviation can be expressed as: $u_t = y_t - \mu - \beta x_t$, where $u_t \sim I(0)$ process and $u_t \sim I(1)$ otherwise (Engle & Granger, 1987). The idea behind ECM consists of extracting valuable information trapped in the residual obtained from the OLS estimation of cointegrated variables (*error term*), and then incorporating that information in the new equation for another estimation (*correcting the model*). Static regression (24) needs to be estimated in the first step of the procedure. We are interested in residuals from this regression, as they are estimates for the u_t series in equation (24). Then we check if this series of residuals is stationary or not, as this is, in fact, the plausible indication that the two series of data used in the estimation are in fact cointegrated. Technically, this is done using a classical DF testing procedure, although, the critical values are different (MacKinnon, 2010). The case to be used in stationarity testing is the one without the constant and the trend, as we are assuming the residual series to resemble a *white noise* process. Formally:

$$\hat{u}_t = y_t - \hat{\mu} - \widehat{\beta}\, x_t \tag{25}$$

$$\Delta\hat{u}_t = \sum_{i=1}^{k} C_i \Delta\hat{u}_{(t-i)} + \pi\, \hat{u}_{(t-1)} + \eta_t \tag{26}$$

I conducted the actual estimations of equations (24) and (26) using the already mentioned statsmodels module within the Jupyter Notebook programming environment. In total, twelve estimations were done for both of the equations: Six that cover the US market with the series of *Jet fuel 54* quotes regressed on each of the Futures Contracts series[12], and another six that cover the European market with the *ARA Jet fuel* quotes used as the dependent variable and the series of futures on Brent and Gasoil as the independent ones. Each of the estimations produced their own series of estimated residuals, which were then used in stationarity testing according to equation (26), where the number of regressors was chosen automatically by the software, based on the AIC values. The null of a unit-root was rejected at 5% significance level in each of the tests run, with the critical value for the calculated test statistic being determined as suggested by the referent literature (MacKinnon, 2010), which suggests that the series of all of the futures quotes and jet fuel series are in fact cointegrated. This allows us to proceed to the second step of the ECM.

The second step consists of estimating the equation that incorporates the error-correction term as one of the explanatory variables. For the purposes of this thesis, I estimated the following equation:

[12] Both series of data used in this and subsequest regressions were in fact the *ln* forms of the original values.

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \beta_2 \varepsilon_{t-1} + \beta_3 \Delta S_{t-1} + \beta_4 \Delta F_{t-1} + u_t \quad (27)$$

The said equation incorporates the lagged effects of the percentage-changes in growth rates of both of the dependent and independent variables, to reflect the typical form of the ECM. I am interested primarily in the estimate β_1, as it represents the optimal hedge ratio for each and every commodity futures' series. Estimate β_2 shows how long run equilibrium in prices' evolution is re-established, after a price shock in the previous period. In the Table below, we have the estimated parameter values for the US market:

Table 8: ECM estimates – US market

	WTI Crude Oil			NY Harbor ULSD		
	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month
α estimate	~ 0	~ 0	~ 0	~ 0	~ 0	~ 0
p value	0.98	0.97	0.87	0.97	0.97	0.91
β_1 estimate	0.759	0.796	0.836	1.002	1.059	1.062
p value	0.00	0.00	0.00	0.00	0.00	0.00
β_2 estimate	0.017	0.017	0.014	0.048	0.049	0.042
p value	0.00	0.00	0.00	0.00	0.00	0.00
β_3 estimate	- 0.03	- 0.06	- 0.04	0.047	0.054	- 0.05
p value	0.29	0.04	0.19	0.13	0.11	0.07
β_4 estimate	0.011	0.054	0.04	- 0.04	- 0.07	0.02
p value	0.7	0.06	0.19	0.2	0.02	0.53
Adj. R-squared	0.617	0.624	0.615	0.831	0.787	0.738
Dep. Variable:	Jet fuel 54					

Source: Own work.

The data obtained from the model's estimation are quite similar with those obtained in the simple OLS estimation in *Table 6.* Namely, the optimal hedge ratios for the WTI futures are almost the same in both of the models. Given that we have more than one explanatory variable in the equation, I present the obtained adjusted R^2, which is not significantly higher from R^2 obtained in OLS. The situation is similar with the results of the heating oil futures – although the adjusted R^2 are slightly higher, suggesting that the ECM fits the data better. The estimated optimal hedge ratios are practically the same. For both WTI and heating oil futures' models, we can observe that the estimates of the cointegrating factor are positive and statistically significant, but their values in all the cases are close to zero. Finally, the results also suggest that none of the other explanatory variables, have statistically significant influence in the jet fuel price determination. We can now proceed to the results of the ECM estimation in the case of the European jet fuel market:

Table 9: ECM estimates – European market

	Brent crude			Gasoil		
	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month
α estimate	~ 0	~ 0	~ 0	~ 0	~ 0	~ 0
p value	0.91	0.83	0.73	0.98	0.91	0.81
β_1 estimate	0.622	0.627	0.619	0.919	0.900	0.906
p value	0.00	0.00	0.00	0.00	0.00	0.00
β_2 estimate	0.058	0.057	0.033	0.061	0.065	0.029
p value	0.00	0.00	0.00	0.00	0.00	0.00
β_3 estimate	- 0.26	- 0.25	- 0.22	- 0.22	- 0.24	- 0.12
p value	0.00	0.00	0.00	0.00	0.00	0.00
β_4 estimate	0.349	0.349	0.33	0.19	0.21	0.09
p value	0.00	0.00	0.00	0.00	0.00	0.00
Adj. R-squared	0.542	0.527	0.485	0.804	0.729	0.690
Dep. Variable:	ARA Jet fuel					

Source: Own work.

The optimal hedge ratios estimated by the ECM for the European market are all slightly higher in absolute terms compared to those estimated by the OLS. Their values remain almost the same, regardless of the differences in futures' maturities. Compared to the findings from the US market, the ECM performed on the European data produced statistically significant parameters for all of the explanatory variables (disregarding the constant term). Adjusted R^2 was higher in any of the ECM regressions than the respective R^2 reported in *Table 7.*

4.4 Measuring hedge effectiveness

In this part of the thesis, I try to determine which of the commodity futures series that we considered in the previous analysis produces the most effective hedge for the prospective hedger. The idea of an effective hedge programme might be intuitively clear to a certain extent but as will become clearer in the text that follows, it is important to establish what exactly is meant by *hedge effectiveness*. Namely, the literature defines hedge effectiveness as: "the proportion of the variance that is eliminated by hedging" (Hull, 2015 p. 60). By reducing, or even eliminating, the variance in expected payments for jet fuel expenses, management stabilises the expected cash outflows and makes the entire cashflow more predictable, which, in turn, makes it possible for the company's liquidity requirements to be satisfied under the optimal terms. Hedge effectiveness can also be defined in a somewhat more practical sense as "the extent to which changes in the fair value or cash flows of the hedging instrument offset the changes in the fair value or cash flows of the hedged item" (KPMG, 2015 p. 2).

In order for the gains and losses of the financial derivatives used for hedging to be reported concurrently with the earnings and losses originating from the risky assets (those that are being hedged), and not only at their maturity, the company must somehow be exempt from the general accounting rules. This is done by employing hedge accounting. Obviously, without such treatment of the hedging derivatives' earnings, the reported earnings of a company in any given period would only tell half of the story, not to mention that it could happen that the shareholders would disapprove any future hedging practise simply because the benefits of the one taken previously were not reported accurately. In order to qualify for the practice of hedge accounting, the company must prove to the auditors that their hedge programmes are *effective enough.* One of the referent quantitative indicators of an effective hedge is the coefficient of determination (R^2) from a regression of the hedged item on the hedging derivative of 0.8 or more. An effectiveness assessment has to be conducted and reported at least quarterly, for as long as the hedge programme is in place (KPMG, 2015).

Analysing the complete set of rules and requirements for employment of hedge accounting is out of the scope of this thesis, but the idea of comparing R^2 values obtained from regressions I already conducted may be a good way of determining the optimal derivative to be used in jet fuel hedging on the US and European markets. However, simply comparing those R^2 values, in order to determine derivatives' optimality, would, strictly technically speaking, be inaccurate. This is because coefficients of determination are referent only if the company decides to hedge their exposure exactly according to the optimal hedge ratio calculated in any of the respective regressions (Kawaler & Koch, 2013). Given the fact that, as per equation (3), the potential hedger would need to round the number of futures to be used in the actual hedging programme, he would, consequently, be changing the optimal hedge ratio slightly. Therefore, it might be more accurate, to compare the derivatives' potential by calculating and comparing the *R^2 analogue* value according to equation (18), for every one of the calculated models.

For this purpose, I will calculate and compare the said measure, by using the hedge ratios already calculated in the OLS and EMC regressions. The values will be calculated on the basis of the price data from the last quarter of 2019. To account for the slight adjustment of the optimal hedge ratios, I will be rounding the R^2 to the first decimal. Even though I am aware that a more realistic, albeit computationally demanding calculation, could be performed, I believe that this adjustment suffices for the purpose.

For the easier understanding, I am repeating the formula for *R^2 analogue* presented in detail earlier:

$$R^2\ analogue = 1 - \frac{SSE}{SST} \tag{17}$$

$$SSE = \sum (\Delta S_t - \beta^* \Delta F_t)^2 \tag{18}$$

$$SST = \sum (\Delta S_t - mean(\Delta S_t))^2 \tag{19}$$

The *Table 10* contains calculated *R^2 analogue* values, rounded to 5 decimal points for both models together. This combining of the results in the same table was done simply to avoid presenting the same numerical data for both OLS and ECM models separately. Namely, the estimated optimal hedge ratios *(β)* obtained by OLS or ECM estimation technique are so similar that the calculated *SSE* and *SST* components within *R^2 analogue* values appear identical when rounded to the fifth decimal point. This is the case for each of the derivatives' series (3, 6 and 12-month maturities).

Table 10: R^2 analogue values for OLS and ECM

OLS / ECM	WTI Crude Oil			NY Harbor ULSD		
	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month
SSE	0,00468	0,00468	0,00468	0,00210	0,00344	0,00160
SST	0,02787	0,02787	0,02787	0,02787	0,02787	0,02787
R-squared analogue	0,83221	0,83221	0,83221	0,92474	0,87671	0,94247

OLS / ECM	Brent crude			Gasoil		
	3 - month	6 - month	12 - month	3 - month	6 - month	12 - month
SSE	0,00886	0,00848	0,00848	0,00480	0,00382	0,00382
SST	0,02834	0,02834	0,02834	0,02834	0,02834	0,02834
R-squared analogue	0,68737	0,70073	0,70073	0,83054	0,86513	0,86513

Source: Own work.

If we compare the *R^2 analogue* values within the same group of derivatives, we observe that in this data sample, series of different maturities produce almost the same levels of effectiveness. This means that there is no compelling evidence that the series of futures quotes with shorter maturities give necessarily better results - which is what one would expect, given the values of adjusted R^2 from Tables 8 and 9.

Now we can compare the performance of the groups of commodities in different markets. The results are clear in this case and they indicate that the futures on fuel derivatives, rather than those on crude oil, consistently provide higher values of *R^2 analogue* in both of the markets. This means that a prospective hedger should always opt for a hedge programme using heating oil futures as opposed to those on the crude oil in both the US and European markets. That being said, we observe that the heating oil futures sold in NYMEX perform particularly well, with *R^2 analogue* values higher than those of any other considered instrument.

What we can also see is that the resulting R^2 *analogue* values do not differ between the futures series used in OLS and ECM. This is because the optimal hedge ratios, estimated using these models and my data sample, are not too different one from the other in absolute values. This finding is rather interesting and somewhat counterintuitive, as it indicates that, although ECM should be used in optimal hedge ratio estimation, given the reasonable assumption of cointegration, a prospective hedger could construct his hedge programme around the estimates obtained from OLS and still expect an effective hedge.

Finally, Table 10 reveals another interesting finding. The measure of the hedge effectiveness – the R^2 *analogue*, is consistently above 80% for all of the Futures Contracts except for those on Brent crude. Technically, this means that the potential hedger would most likely satisfy the requirements for the hedge accounting use, as long as he used Futures Contracts on WTI Crude Oil and NY Harbour ULSD if he was based in the US, or futures on Gasoil if he was based in Europe.

5 COVID-19[13] PANDEMIC AND THE GLOBAL AVIATION INDUSTRY

If we were to choose a single, most significant event that marked the year of 2020. on the global scale, that would without any doubt, be the outbreak of COVID-19. The disease is caused by a virus from the family of coronaviruses and is referred to scientifically as: Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) (Mayo Clinic, 2020). The disease is characterised by flu-like symptoms, such as a high fever, tiredness and a dry cough. Although the majority of the infected individuals only develop mild to moderate symptoms, older adults and people with existing chronic medical conditions are at greater risk of developing severe complications that can lead to death. The virus was first isolated and identified in the Hubei province in China in December 2019, but as our modern world is so well connected, many other countries reported their first case of infections immediately afterwards. In fact, it only took a bit over 3 months for the World Health Organization (WHO) to declare the pandemic on March 11th, 2020 (WHO, 2020). At the moment of writing this thesis (February 2021), there have been more than 100 million reported cases of infection globally, with more than 2 million deaths linked directly to the disease (WHO, 2020; WHO, 2020).

Currently, the COVID-19 pandemic is still raging vigorously, and the treatment is mostly symptomatic. Several vaccines have been approved for use, and now the countries are racing to secure a sufficient number of units from their preferred suppliers. The economic, social and political effects of the pandemic are profound and numerous, and as the pandemic has

[13] In COVID-19, ”CO” stands for ”corona”, ”VI” for ”virus”, ”D” for ”disease” and ”19” for the year of 2019, as the virus was first identified in Wuhan, PR China in December 2019.

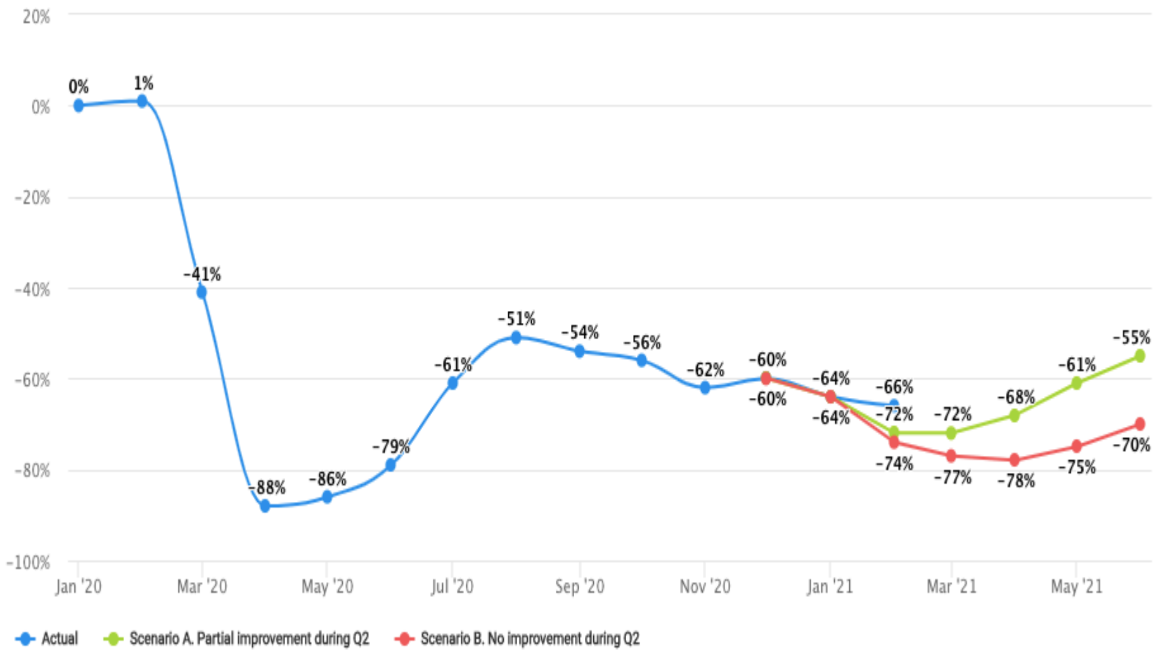
not been ended, we shall remain patient to see what a year-long battle with the disease will amount to.

Given that one of the initial measures taken to contain the infection on the local and national levels was restricting movement of the people, civil aviation was negatively affected immediately. The prohibition of leaving one's region of residence was first announced in the Hubei province in China, where the virus is believed to have originated, but the international community reacted quickly and forbade international passenger flights to and from China and other countries with a high incidence rate, as it became evident that the air transport is likely to be the source and catalyst of the infection spreading internationally (Lau, et al. 2020). The restrictions have, since the initial proclamations, changed many times. This has made flight planning particularly difficult. The air operators have had difficult task of arranging schedules, crew rostering, buying and maintaining airport slots for flights that might become unfeasible with a single governmental announcement. During the summer months of 2020, when the infection seemed to have weakened in some parts of the world, non-essential travels were again allowed, which was the perfect opportunity for air operators to try and bank at least some of their planned 2020 incomes. For instance, Figure 7. shows the percentage change in the number of flights handled by the EUROCONTROL[14] compared to the respective months in 2019. Although EUROCONTROL records activity over a specific region only, the findings are still representative of the global aviation market as the region itself is quite heterogeneous - it consists of the EU & EFTA Member States, the Balkan countries, Turkey, Armenia and Georgia.

Air traffic showed a significant and steep recovery during the summer months, and it seemed that reaching the pre pandemic scale of operations would be feasible, even before the beginning of 2021. However, faced with the growing numbers of the newly infected individuals during the autumn, and the subsequent reintroduction of the travel restrictions within the Member States, EUROCONTROL had to revise its projections of the air traffic recovery downwards several times. The end of 2020 was also characterised with identification of new, regional, more infectious variants of the virus, which led to the introduction of even stricter travel restrictions. Together with delays in vaccines' deliveries and uneven immunisation roll-out, this all called for new and gloomy scenarios of recovery. As per the last available Air Traffic Report, January 2021 recorded about 65% fewer flights compared to January two years prior, and if the optimistic scenario is realised, this year's Q2 activity levels will not differ significantly from that of the year before, which makes it only about 45% of that in 2019. If, despite the vaccinations and reduction in the number of newly infected individuals, countries decide not to relax their entry restrictions, we could be looking at merely 25-30% of the air traffic recorded in the year before the pandemic was declared (EUROCONTROL, 2021).

[14] European Organisation for the Safety of Air Navigation, commonly known as EUROCONTROL is an international organisation that provides air traffic management services across Europe, with the exception of Belarus and Russia.

Figure 7: Air traffic recovery scenarios (base year 2019.)



Source: EUROCONTROL (2021).

As an industry characterised by significant capital requirements and a high share of the fixed-cost component in their total expenses, many airlines faced devastating liquidity issues and eventually declared bankruptcy within the first couple of months of the pandemic (Bloom, 2020). Big airlines, national carriers as well as those with a significant negotiating power, seem to have managed to survive the first 12 months since the pandemic was announced, but only after streamlining their operations, receiving significant financial aids from their respective governments, and temporarily, even adjusting their business models. In the following text I will try to present some of the most interesting examples from the industry, which show how this unforeseen situation forced the airlines to rethink their operations, remodel their businesses, and maybe even reinvent the whole industry.

1. Immediate retiring of wide-body aircraft

Country-specific, COVID-19 related entry restrictions are changing rapidly and in an unpredictable way, which is why the airlines have a hard time planning routes with satisfying load factors. Having to do the same thing with wide-body aircraft makes things even more challenging. Such big aircraft demand significant logistics in the flight preparation stage, consume huge amounts of fuel even on relatively short routes, and require costly maintenance inspections available at only a handful of sites, just to stay airworthy. All that, coupled with the crippled and weak demand in flying passengers, made many airlines consider retiring their Boeing 747s and Airbus 380s much sooner than initially planned (Weiss, 2020). In fact, Boeing's CEO, David Calhoun, announced the ceasing of production of the legendary B747 type following delivery of the pending orders in 2022 (Boeing, 2020).

2. Change of operational focus

As governments began to lift country specific entry requirements during the early summer months, many airlines saw this as a perfect opportunity to profit from operations to the tourist resorts. Leisure demand picked up quickly and sharply, while the business demand barely increased at all, which is no surprise given that many offices are still closed, conferences are still being cancelled and clients are still cautious. This meant effectively that the airlines had to respond by reducing their capacities quickly from where people travel for work and adding them to where people travel for vacation. This is not a particularly difficult task for the European operators, especially those registered in EU countries, as commercial flights within the EU do not require lengthy administrative approvals for scheduled, commercial operations, and this increase in the demand for flights to Southern Europe is a situation that happens every summer, and is accounted for by the yearly plan of operation. For the US legacy carriers, who operate mostly on the basis of the hub-and-spoke network, shifting a significant portion of their network at such short notice, with new city pairs being introduced relatively quickly can be quite resource demanding. This requires renegotiating terms of fuel supply, Catering Contracts with new suppliers present at the new locations, hotel accommodation for the crew, etc. This all puts certain operators, such as Southwest Airlines, who have traditionally relied on more leisure-oriented demand, in a better position to conquer the market. This, however, does not mean that the airlines outperformed the 2019 summer season by any means (IATA, 2020).

3. Flying cargo flights

At the very beginning of the coronavirus pandemic, many passenger airlines, changed their main business activity temporarily from passenger to cargo transport. National governments used to charter passenger airlines for the purpose of transporting large quantities of medical and Personal Protection Equipment (PPE) from China to their respective countries in the first months of the pandemic. Both scheduled and non-scheduled airlines, as well as the general aviation operators, may be authorised to transport cargo load with or without the passengers by their respective national authorities. Supplying national governments and other clients with PPE was, therefore, compliant with their Air Operator's Certificates (AOC), but this does not mean that flights of this kind were easy to organise. Loading bulky and heavy boxes in the cabin moves the centre of balance of the aircraft in an unusual way and necessitates special kinds of belts and nets to immobilise the payload effectively. The European Union Aviation Safety Agency has, therefore, issued a set of Guidelines for the operators who intend to organise such flights (Ottomaniello & Ohnimus, 2020).

By the end of 2020, national governments world-wide quickly pledged to immunise significant proportions of their respective populations as soon as possible, which created a new, potentially highly lucrative niche in the global aviation market. Ensuring reliable cooling of the vaccine with packs of dry ice, however, created a logistical nightmare for the operators. This is because carrying dry ice on board the aircraft is indeed a serious safety concern, as it introduced the risk of explosion and oxygen deficiency in the cabin in case the packaging is improper. For these reasons, EASA and the FAA have both published extensive Guidelines for risk mitigations that the operators must follow strictly (EASA, 2020) (FAA, 2020).

4. Oil price reduction

The global oil market has been oversupplied for the last 5 years - ever since the US flooded the market with oil from its shale deposits and OPEC deciding not to coordinate and reduce their output in early 2015. With the pandemic suffocating the world's economy and most of the countries imposing various types of travel restrictions with no clear signs of when they would be lifted, the global demand for oil was decreased abruptly and significantly. This alone would inevitably cause an immediate fall in spot prices of oil globally, but there was additional event that amplified the effect of insufficient global demand for oil and refined fuels. Namely, in early March 2020, OPEC and Russia failed to reach an effective agreement to continue limiting their respective oil production, past the first quarter of 2020. This triggered the United Arab Emirates and Saudi Arabian producers to announce increases of their respective daily production capacities (ADNOC, 2020) (ARAMCO, 2020).

In the highly connected and globalised oil market, such events reverberate quickly and reach local markets, causing disturbances. In case of the US domestic oil market, for example, this culminated with an event that was thought to be even theoretically impossible. Namely, huge quantities of domestic oil that were now increasingly difficult to be sold internationally started filling storage sites all over the country - most importantly the nation's largest facility of this kind and the NYMEX delivery point in Cushing Oklahoma. When the industry analysts published reports on no vacant storage come May 2020, panic among the hedgers had already done the damage (Kearney & Kumar, 2020).

Figure 8: WTI crude oil futures for May 2020 delivery (USD / barrel)

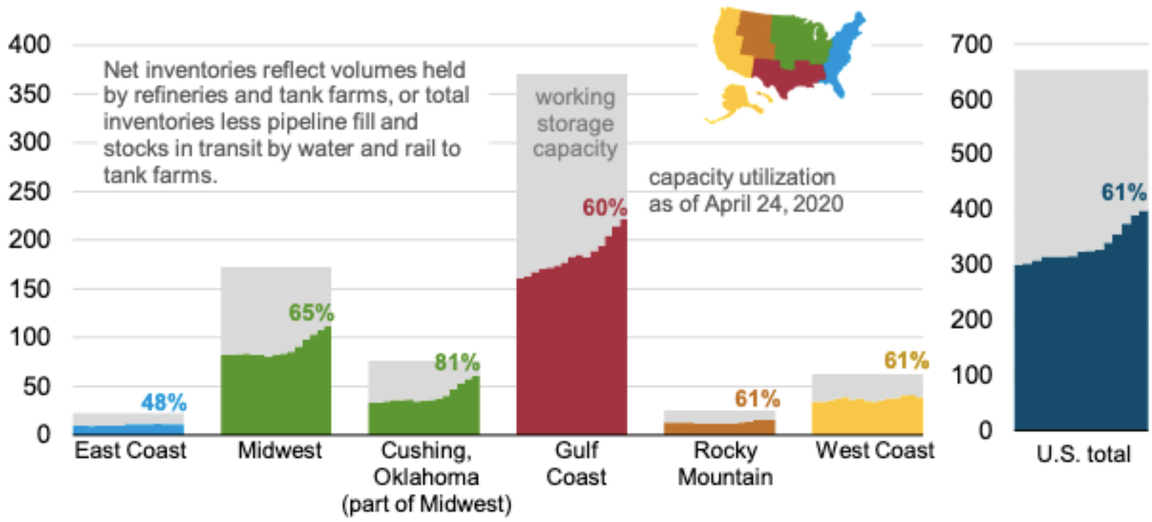
Adapted from EIA (2020c).

On Monday, April 20th, NYMEX traded WTI futures for May delivery fell below zero dollars per barrel for the first time in history, ever since the trading began in 1983. Although the price rebounded above zero the following day already, this episode revealed interesting mechanics that characterise commodity futures markets. Even intuitively, it is difficult to imagine that an important and precious commodity such as crude oil, trades at negative prices. While titanic and historical, this event occurred locally, lasted briefly and did not impact the spot market significantly. Nevertheless, it had a potentially devastating effect for all the oil hedgers who did not adjust their portfolios quickly enough. A particularly curious thing in the whole story is that the crisis was caused by the rigid, yet universal features, of all commodity futures.

The Contract for May delivery was set to expire on April 21st, which means that whoever had not closed their long position the day prior, would have to take physical delivery of WTI crude oil in Cushing, Oklahoma and nowhere else. Exceptionally though, the CME group gave an option to the investors to settle their open positions through privately negotiated and off-exchange executed settlements referred to as Exchange for Related Position Transactions (EFPT), that could be activated shortly after the futures trade was closed. EFPTs are then, subsequently, submitted to the Exchange for clearing purposes (CME Group, 2020b).

Although the storage facilities at the delivery site were actually not physically completely occupied, except for the compulsory free space that is needed for normal operation of the pipeline, almost all the other free space was already leased. The hedgers who did not manage to close their long positions prior to the futures' last trading day, could now either close their open position at a significant discount through EFPT and avoid taking delivery of the oil, or they could try to sub rent already leased storage capacities and receive the crude that they did not need nor had buyers for.

Figure 9: US net crude oil inventories (Jan 17 – Apr 24, 2020) in millions of barrels



Adapted from EIA (2020d).

Interestingly, ICE traded futures on Brent crude oil never sank nearly this much, regardless of the commensurate drop in the demand for oil and oil derivatives that affected the European market in the same period. Some analysts point out, that this could be simply because the futures on Brent crude give certain flexibility, allowing for oil delivery in a variety of sites within the ARA region, which allows the market itself to avoid bottlenecks (Constable, 2020).

With travel restrictions still in place and the pandemic far from being over, airlines were facing the seemingly impossible task of planning this year's fuel programme. Not only is it difficult to target the price of jet fuel, but even the rough estimates on the quantity of jet fuel that will be needed is far from reliable. In the first year of the pandemic alone, the European based operators reported a staggering $4.7 billion in losses on their hedge programmes (Lewis, 2021). In such conditions, the arguments for not hedging jet fuel expenses altogether, seem to be stronger than ever.

CONCLUSION

In this thesis, I have tried to analyse the specific way of jet fuel hedging: Hedging with Commodity Futures Contracts. The idea behind this was to present step-by-step guidelines to executives in the airline industry, or other professionals who are considering hedging their jet fuel expenses in this way. I was particularly interested in explaining how important theoretical concepts translate into work with the real data. The optimal hedge ratio was identified as the most important numerical relation between the price of jet fuel and the hedging instrument. This relation was estimated using real data series, and for this I used two different procedures: OLS and ECM. These procedures differ in complexity, as the ECM requires additional steps, but assures correct specification of the estimating equation.

Somewhat surprisingly, the obtained results accord with the research papers that cover this topic only to a certain extent. Results for both US and the European markets show that the futures on heating oil rather than those on crude oil, provide a superior hedge. Although this finding might be intuitive, given the chemical similarities between jet fuel and heating oil, we must be reminded that the crude oil market is far more developed, and that alone ensures better conditions for more efficient price adjustments. If we look at this situation from a slightly different perspective however, one could argue that the airlines in the US or Europe have an advantage over the other operators simply because futures markets on oil derivatives are better developed there then elsewhere, all things being equal.

Contrary to my expectations, the data sample used in this research did not provide strong evidence that the contracts with shorter maturities provide necessarily better results. This finding was somewhat unexpected as it suggests that even the operators who do not adjust their portfolios frequently, can expect the same level of protection from their hedge programmes as those attentive hedgers - who do. Finally, perhaps the most interesting result in this research is the one concerning model specification. According to the chosen measure of the hedge effectiveness, in this data sample there was no evidence that the ECM provides significantly better estimates of the optimal hedge ratios compared to the OLS, even in the case of likely cointegration between the series. This result could be due to the time frame that was chosen for this analysis, the length of the series used, or both. In any case, this finding may encourage professionals in the industry to consider computationally less demanding methods for establishing their future hedging programmes.

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APPENDICES

Appendix 1: Povzetek

Letalsko gorivo je pomemben del obratovalnih stroškov vsake letalske družbe. Z namenom zmanjševanja likvidnostnih stroškov in zagotavljanja maksimalne vrednostne rasti svojim interesnim skupinam vodstveni kadri nenehno iščejo načine nadzora stroškov goriva.

Na voljo so številne metode, odvisne od specifičnega položaja letalske družbe na trgu, njene pogajalske moči, vrsto operacije, tržne niše, pa tudi velikosti, starosti in raznolikosti flote. Cilj magistrske naloge je podrobno preučiti enega od načinov varovanja pred naraščanjem cen letalskega goriva – varovanje pred tveganjem z blagovnimi terminskimi pogodbami.

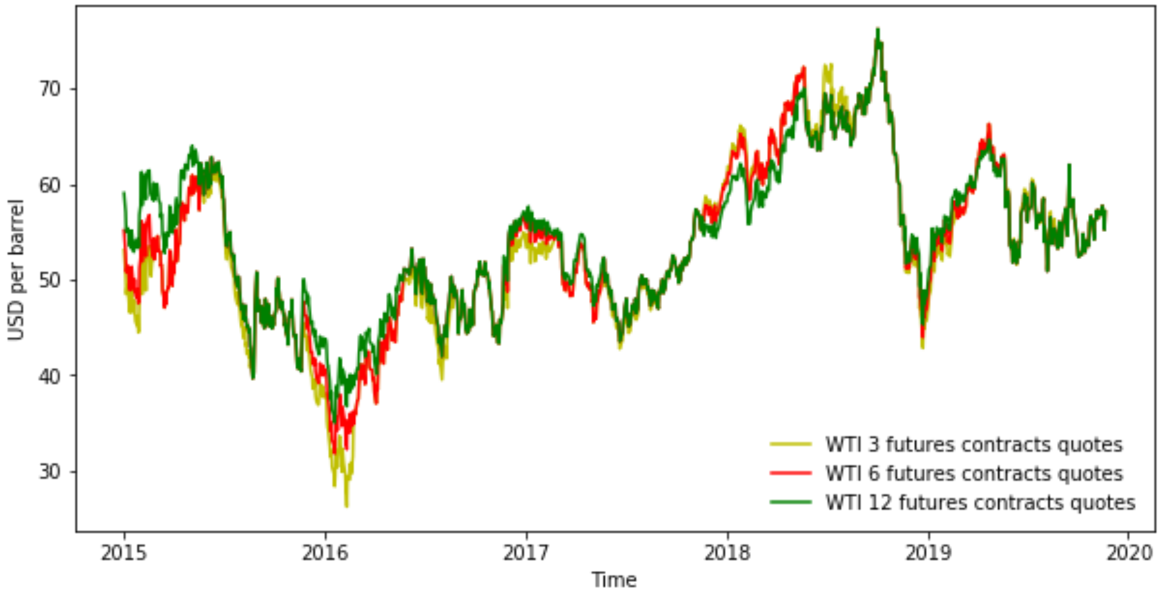
Rabo terminskih pogodb ali katerih koli drugih finančnih instrumentov z namenom varovanja pred tveganjem imenujemo finančno varovanje pred tveganjem. Lahko se ga uporablja samostojno ali v kombinaciji z operativnim varovanjem, ki vključuje raznolike dejavnosti ki segajo od racionalizacije vsakodnevnih procesov pa vse do optimizacije strukture flote.

Uporaba blagovnih terminskih pogodb v ta namen se izvaja v več korakih. Najprej je potrebna temeljita analiza finančnega trga, pri čemer mora letalska družba določiti najustreznejšo blagovno terminsko pogodbo. Ustreznost finančnega derivata se določa glede na njegovo likvidnost in cenovno korelacijo s ceno letalskega goriva. Magistrska naloga obravnava terminske pogodbe najpogosteje uporabljenih tipov surove nafte in njenih destilatov, ki ustrezajo obema pogojema.Pri tem moramo pri pogodbah upoštevati tudi rok zapadlosti, saj terminske pogodbe z različnimi roki zapadlosti na promptnem trgu konvergirajo z različnimi stopnjami, kar lahko v določenih primerih privede do nepotrebnih stroškov.

Na koncu se vzpostavi še povezava med številom potrebnih terminskih pogodb in ceno določene količine goriva, ki jo je v danem obdobju potrebno zavarovati pred tveganjem, s pomočjo specifičnega parametra imenovanega optimalno razmerje varovanja. To razmerje lahko ocenimo z različnimi ekonometričnimi metodami, ki se med seboj razlikujejo v zapletenosti in zahtevajo specifično pripravo podatkov. Pričujoča magistrska naloga jasno razlaga logiko vseh prej omenjenih korakov, ob tem pa poskuša postreči z uporabnimi pojasnili, ki, po avtorjevih najboljših močeh, statistiko, ki se skriva za navedenmi formulami in izračunanimi koeficienti prevajajo v prakso. V zaključnem delu naloga predstavi nekaj ključnih sprememb v letalski industriji, ki jih je posredno ali neposredno povzročila pandemija koronavirusa.

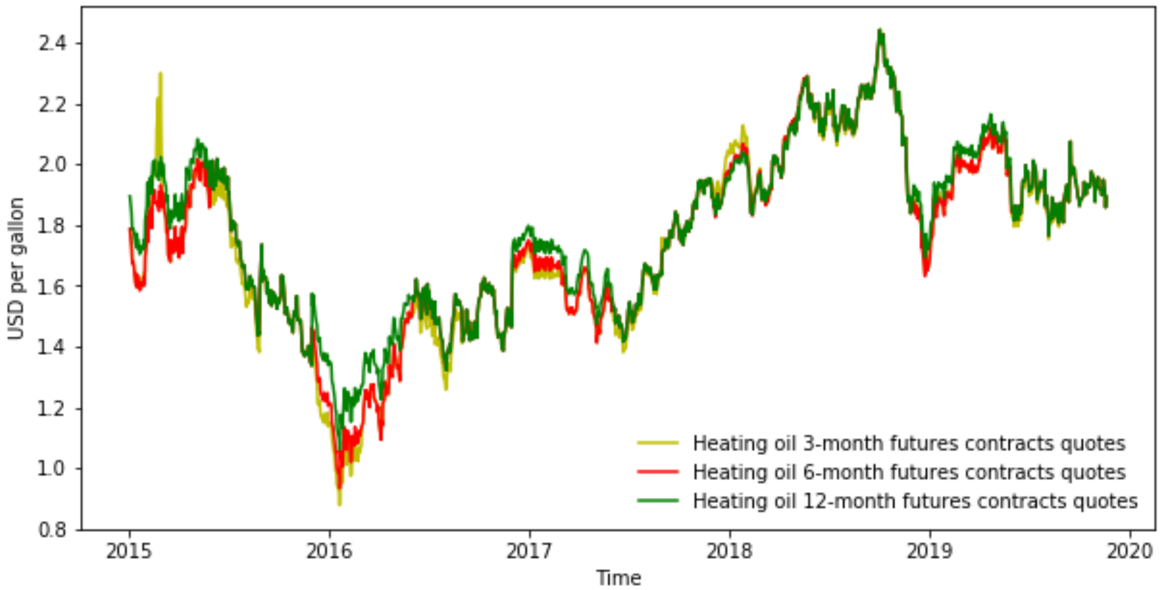
Appendix 2: Suplementary plots

Figure 10: West Texas Intermediate crude oil futures contracts closing values



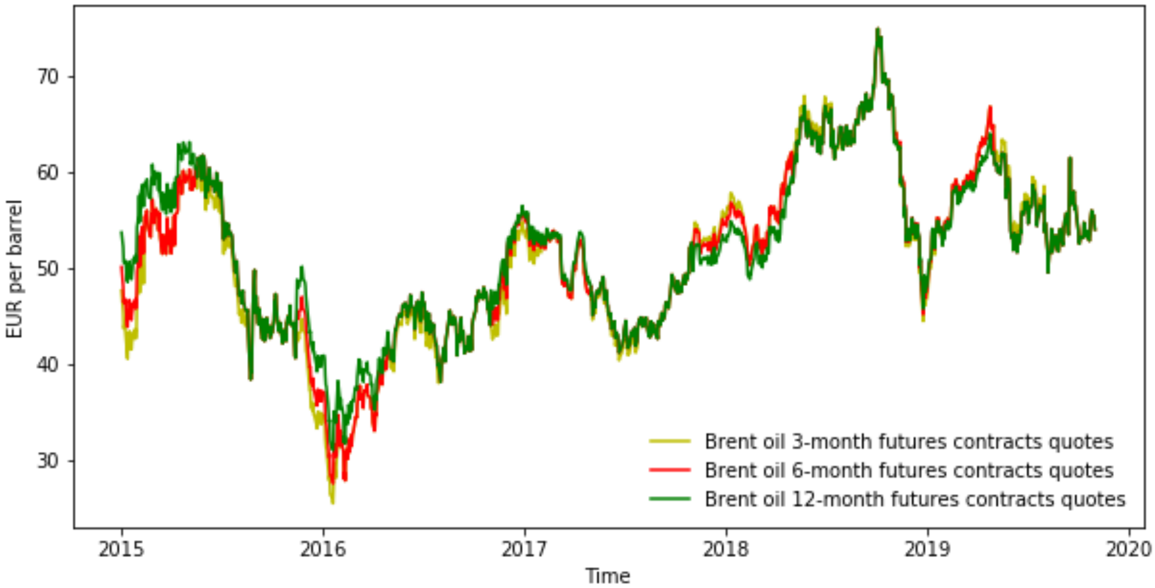
Source: Own work.

Figure 11: ULSD (Heating oil) futures contracts closing values



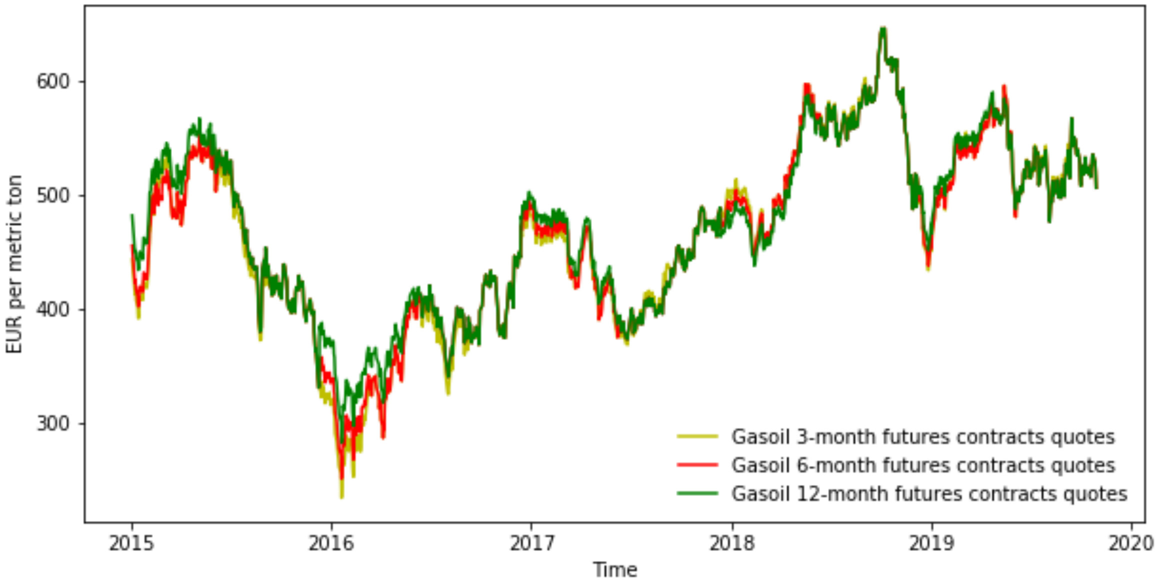
Source: Own work.

Figure 12: Brent oil futures contracts closing values



Source: Own work.

Figure 13: Gasoil futures contracts closing values



Source: Own work.

Appendix 3: Python functions and methods used:

```
#------define function for ADF test---------

def adf_test(timeseries):
    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries,regression='nc',  autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags 
Used','Number of Observations Used'])
    for key,value in dftest[4].items():
       dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
#----- options are: {'c','ct','ctt','nc'} -------



#------define function for kpss test--------

def kpss_test(timeseries):
    print ('Results of KPSS Test:')
    kpsstest = kpss(timeseries,regression='c')
    kpss_output = pd.Series(kpsstest[0:3], index=['Test Statistic','p-value','Lags Used'])
    for key,value in kpsstest[3].items():
        kpss_output['Critical Value (%s)'%key] = value
    print (kpss_output)
#----- options are: {'c', 'ct'} ---------

model = sm.OLS('y variable', sm.add_constant('x variable')).fit()

residuals = model.resid
model.summary()
durbin_watson(residuals)
```